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Low-level human interaction pipeline for identification, monitoring and cataloguing orbital objects from optical observations

PhD

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1. Introduction

The rapid increase in orbital artifacts over recent years has increased the issue of space debris, posing significant challenges to both space agencies and private aerospace industries. The European Space Agency (ESA) estimates that approximately 750000 debris fragments larger than 1 cm are currently orbiting Earth, each representing a potential threat to operational satellites and manned missions [1]. Space collisions not only risk damaging critical infrastructure but could also trigger the so-called Kessler Syndrome, where cascading collisions create even more debris, compounding the problem [2]-[4]. According to the last ESA's Space Environment Annual Report [5], human activities in the space field have resulted in about 17000 satellites launched, and approximately half of these are still functioning. More than 35000 space debris are regularly tracked by the sensor networks located throughout the globe, and there are millions that cannot be tracked due to their small size. All these numbers are destined to increase due to the intensification of the new space race by the private companies with their large constellations made of thousands of satellites, as can be noted in the next Figure 1 from the exponentially increasing number of objects in the last years. The objects are distinguished depending on types: UI = Unidentified, RM = Rocket mission related object, RD = Rocket debris, RF = Rocket fragmentation debris, RB = Rocket body, PM = Payload mission related object, PD = Payload debris, PF = Payload fragmentation debris, PL = Payload.

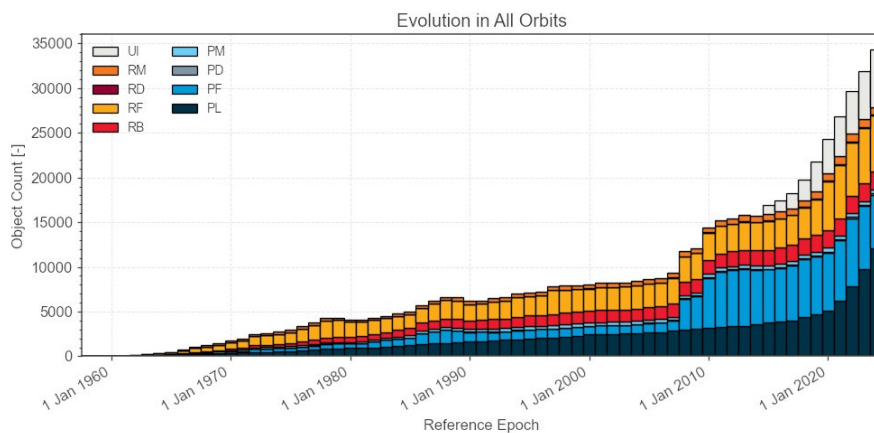


Figure 1. Number of tracked objects in Earth orbit over time (ESA Space Environment 2024).

The high number of uncontrolled Resilient Space Objects (RSOs) in orbit represents a threat not only for the orbiting active satellites, but also for the on-ground population and facilities. The uncontrolled atmosphere re-entries are increasing year by year and not all of the re-entering bodies burn during this phase, raising the possibility of catastrophic events. The next Figure 2 highlights efficiently how these numbers are elevated [5].

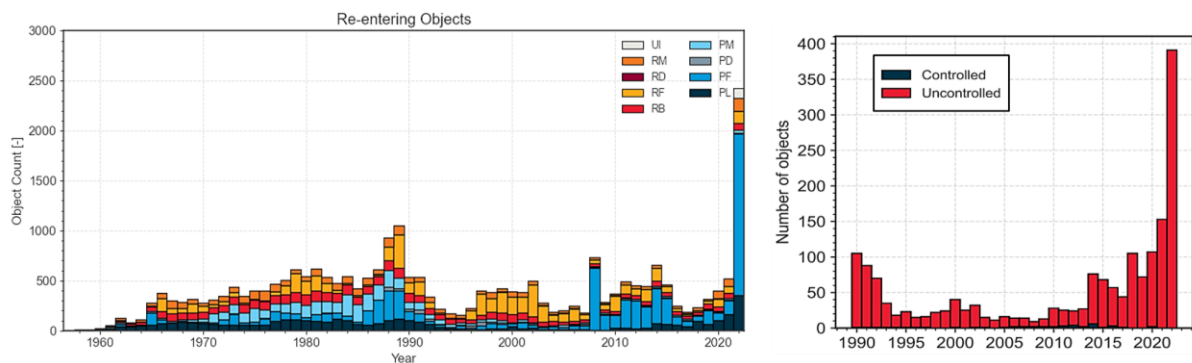


Figure 2. Re-entry objects over years discerned by types, on the left, and by controlled/uncontrolled, on the right

The social and economic well-being of the European population, as well as the safety and security of facilities, are strictly related to space-based activities such as observations, navigation, and communications. The continuous overcrowding of the orbits around the Earth undermines these activities, jeopardising the active satellites with potential in-orbit collision and fragmentations. For this reason, in 2021 the European Union (EU), with Regulation 2021/696 [6], adopted the European Space Programme with the specific objectives of “providing or contributing to the provision of high-quality and up-to-date and, where appropriate, securing space-related data, information and services without interruption and wherever possible at global level” and “maximising the socio-economic benefits, in particular by fostering the development of innovative and competitive European upstream and downstream sectors, including SMEs and start-ups”. Already in 2014, the EU understood the risks of this overcrowding phenomenon by adopting the document “Decision of the European Parliament and the Council Establishing a Space Surveillance and Tracking Support Framework” [7] (“SST European document”, hereafter) for the establishment of a framework for SST support. The

decision sets out specific objectives of the SST support framework, including all the activities aimed to reduce the risks related to: in-orbit operations to avoid collision, to launch of European spacecraft, and to uncontrolled re-entry. To achieve all these objectives, both the “SST European document” in 2014 and the Regulation in 2021 foresaw the creation of an SST Partnership between the European Member-States adopting the establishment “*of a network of Member State ground-based and/or space-based sensors*”.

Nowadays, the most comprehensive and available catalogue of uncontrolled objects is the North American Aerospace Defence Command (NORAD) one. The American institution releases periodically orbital information about the objects in the form of Two Line Elements (TLE), which report, ordered in two strings of code, both a set of Kozai-Brouwer mean orbital elements and a term BSTAR (B^*) referred to the area over mass ratio [8]. Unfortunately, the TLEs cannot be used in Space Surveillance and Tracking (SST) as they characterize the orbital motion of tracked object in a purely theoretical model, which accumulate, during each single orbit, the sum of all the variables not considered by the ideal model [9]. For this reason, after a certain period, the errors accumulated by the TLE become so large that they no longer describe the orbit of the tracked object, resulting in an inaccuracy so large that is necessary to update them through a new series of direct measurements and a consequent release of new TLEs after few hours [10],[11]. Due to the huge number of probabilistic variables that contribute to changing the orbit of an object, any predictive model developed will never describe the rigorous behaviour of the object.

Recent research has shifted toward frequent direct measurements of debris and space assets to characterize the objects, to achieve higher positional accuracy and to improve mathematical models. Such advancements are critical for predicting object behaviour, enabling timely collision avoidance, and supporting the sustainable use of space.

1.1. Motivation and research objectives

Current software for extracting orbital parameters from Space Surveillance and Tracking (SST) images heavily relies on manual intervention, particularly in distinguishing and detecting individual satellite tracks. This reliance on human interaction not only increases the risk of misidentification but also poses significant challenges to integrating such software into autonomous frameworks. Addressing these limitations is essential to meet the increasing demand for accurate, efficient, and automated processing in the context of the growing number of satellites and orbital debris.

The motivation for this research arises from the need to develop a robust system capable of extracting both right ascension (RA) and declination (Dec) angles, as well as light-curve data, from optical observations. Such capabilities are crucial for advancing orbital and attitude determination methodologies. This thesis aims to address the following key objectives:

- **Development of Orbital Determination (OD) routine:** Implementing tools for improving orbital element accuracy for catalogued objects, while also enabling initial orbit determination (IOD) of uncatalogued objects using optical SST data. These capabilities are critical for maintaining and updating space object catalogues.
- **Light-Curve Extraction for Attitude Analysis:** Establishing techniques to extract light curves from series of optical observations, which are integral to attitude determination and monitoring the behaviour of RSOs.
- **Observational Routines for RSO Monitoring:** Designing and implementing procedures to observe RSO passes in various orbital regimes, including low Earth orbit (LEO), medium Earth orbit (MEO), and geostationary orbit (GEO). These routines also include monitoring fragmentation and re-entry events.
- **Automated Software Development for RA/Dec and Light-Curve Processing:** Creating software capable of processing a sequence of frames to extract RA/Dec measurements and light curves with minimal human intervention. This includes the

integration of machine learning (ML) methods to enhance detection accuracy and processing efficiency.

- **Optimization of Attitude Determination Techniques:** Investigating and implementing methods for attitude determination based on extracted light curves, focusing on optimization methods to improve computational efficiency and result precision.
- **SST Database Design and Management:** Developing a structured SST database to store acquired frames, results, and analysis outputs. This database serves as a repository for observational data, supporting both current analysis and future research.

The methodologies proposed in this work are built upon extensive observations, ensuring reliability and robustness in their application. By addressing the outlined objectives, this research aims to contribute significantly to the automation and accuracy of orbital and attitude determination systems, paving the way for advancements in autonomous SST operations.

1.2. Thesis structure

This thesis begins with an introduction that outlines the motivation for the research and sets its objectives. The research starts with the fundamentals of Space Situational Awareness (SSA) and Space Surveillance and Tracking (SST), introducing key concepts such as object astrometry, photometry, and the challenges of image analysis, alongside the methodologies employed in the field. A section is dedicated to the application of neural networks in astronomical image analysis, exploring both their potential and the challenges they present.

Following this introductive part, the thesis details the optical systems used in the research, AWARE, SCUDO and Mini-SURGE, covering their installation, testing, and operational management. The focus then shifts to the development of the pipeline and related software

for frame analysis, detailing its architecture, interface, and deployment, particularly within the AWARE station. A comprehensive section explains the functionalities of the developed APIs, including image calibration, tracking methods, light curve extraction, and orbit determination techniques. The research further explores the integration of neural networks for analysing multiple frames, describing the training processes and the validation of centroid algorithms. Light curve inversion techniques are also presented. Finally, the research investigates feasible options for studying the Molniya population of space debris through observational campaigns, concluding with a discussion on future developments, including machine learning models and performance analysis for attitude estimation. In Figure 3 is shown the activity diagram of the thesis.

The thesis is validated through several observation campaigns, demonstrating the effectiveness of the methods and tools developed.

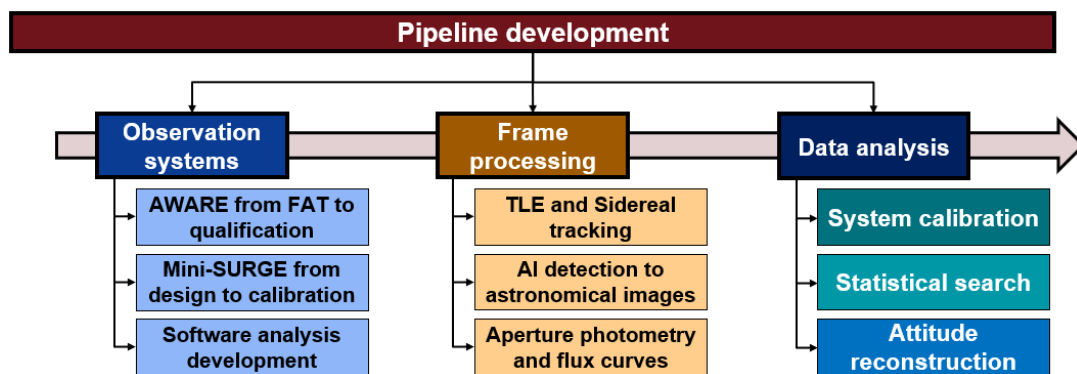


Figure 3. Thesis activities diagram

2. SSA, SST, STM and SDA

In the space environment, maintaining safety, security, and functionality requires a comprehensive understanding of various domains and the implementation of specialized strategies. Key concepts such as Space Domain Awareness (SDA), Space Situational Awareness

(SSA), Space Surveillance and Tracking (SST), and Space Traffic Management (STM) form the foundation for ensuring the sustainable use of space. Each plays a crucial role in mitigating risks and managing the growing number of objects and threats in orbit.

2.1. Definitions

Space Domain Awareness (SDA) defines space as a potential arena for warfare, requiring actionable knowledge to predict, avoid, deter, and adapt to threats in space, as well as recover from and attribute the causes of lost or degraded space capabilities and services. Its main objective is to provide decision-makers with timely and quantifiable evidence of behaviours linked to specific space threats and hazards. SDA covers the full spectrum of activities related to information gathering, processing, and analysis to identify and predict credible threats.

In line with this, the US Space Foundation provides a specific definition of Space Situational Awareness (SSA), emphasizing its focus on understanding and predicting the location of objects in orbit. In particular, according to the US Space Foundation, *"SSA refers to the ability to view, understand and predict the physical location of natural and man-made objects in orbit around the Earth, with the objective of avoiding collisions."* The European Space Agency (ESA) expands this definition, stating that *"SSA aims, ultimately, to enable Europe to autonomously detect, predict and assess the risk to life and property due to man-made space debris objects, re-entries, in-orbit explosions, in-orbit collisions, disruption of missions and satellite-based service capabilities, potential impacts of Near-Earth Objects (NEOs), and the effects of space weather phenomena on space and ground-based infrastructure."*

While SSA provides the broader understanding of the space environment, it is through Space Surveillance and Tracking (SST) that the practical aspects of monitoring and tracking orbital objects are realized. By employing advanced sensors and technologies, SST ensures

the continuous detection and cataloguing of objects, forming the operational backbone for maintaining space safety.

Building on this, effective management of space traffic is essential to ensure the long-term sustainability of space activities. Space Traffic Management (STM) addresses this need by implementing technical and regulatory measures to monitor, coordinate, and govern the safe and responsible use of space.

SDA, SSA, SST, and STM are closely interconnected as shown in Figure 4, each playing a critical role in maintaining space safety and security. SDA provides a strategic framework that encompasses the detection, identification, and prediction of space threats, feeding into SSA's focus on understanding the physical environment and behaviour of objects in orbit. SST operationalizes SSA by employing technologies to detect, track, and monitor space objects, generating the essential data needed for both SDA and STM. STM, in turn, relies on the data and insights from SDA, SSA, and SST to establish guidelines and regulations that ensure the safe coordination of space activities, mitigating the risks of collisions and space debris. Together, these domains form a comprehensive approach to managing space operations, addressing both immediate concerns and long-term sustainability.

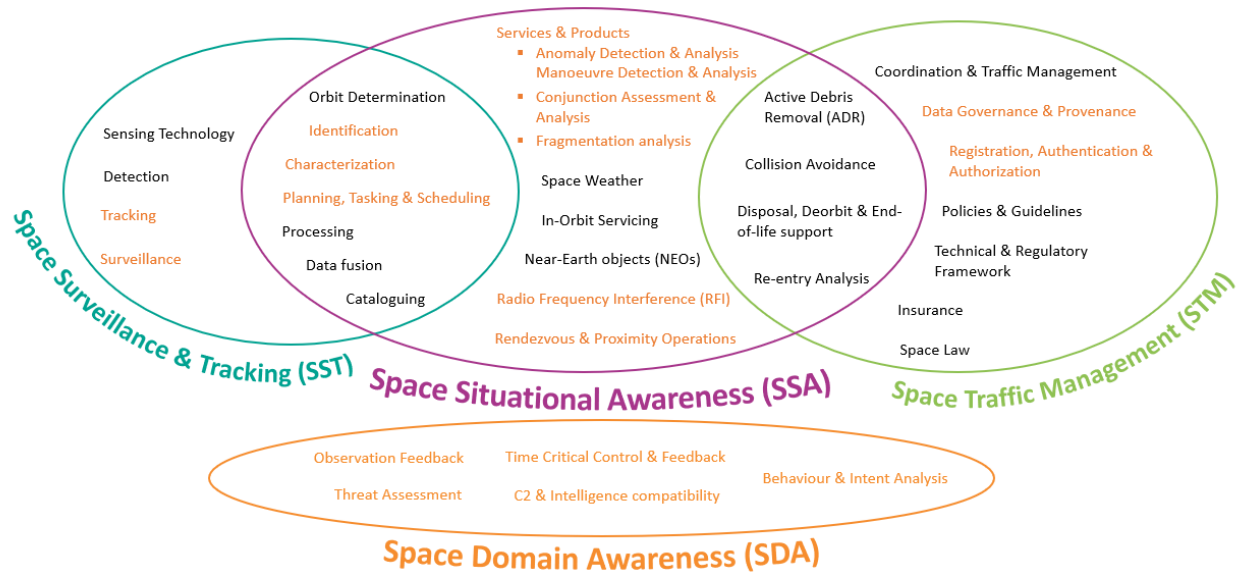


Figure 4. Main activities grouped for each domain

Objects in Earth's orbit encompass a wide range, including operational satellites and constellations that are controlled and managed from the ground, as well as uncontrolled and non-cooperative objects such as space debris. While satellites and constellations are designed with specific missions and controlled trajectories, space debris consists of fragments from collisions, explosions, or disintegration of satellites and rockets, and poses a growing threat. Studying and monitoring space debris is crucial for protecting operational space assets, as these fragments can cause significant damage or even destroy functional objects in orbit. A thorough understanding of the distribution and behaviour of space debris is essential for developing effective mitigation strategies and ensuring the safety and longevity of space missions and critical infrastructure.

The definition of space debris by the Inter-Agency Space Debris Coordination Committee (IADC) [12] is "All man-made objects including fragments and elements thereof, in Earth orbit or re-entering the atmosphere, that are nonfunctional.", while for National Aeronautics and Space Administration (NASA) is "Any human-made object in orbit about the Earth that no longer serves a useful function. Such debris includes nonfunctional spacecraft, abandoned launch vehicle stages, mission-related debris, and fragmentation debris" and for Flury et al. is "Any man-made Earth-

orbiting object which is non-functional with no reasonable expectation of assuming or resuming its intended function, or any other function for which it is or can be expected to be authorized, including fragments and parts thereof” [13].

Current capabilities in both LEO and GEO are insufficient to address the growing demands for monitoring and managing space objects. The limitations stem from several factors, including the size of objects, which makes detection and tracking especially challenging, particularly for smaller objects in GEO. Tracking, predicting, and characterizing objects is hampered by atmospheric interference, instrument bias, noise, and the difficulty of accurately fusing data from different sources. These issues are compounded by the involvement of multiple actors, leading to inconsistencies in data quality. Moreover, the lack of effective solutions for tracking small objects in GEO increases the risk of collisions. The current systems also generate too many false alarms and miss potential collision risks due to inaccuracies in the data, further complicating space traffic management. In Table 1 are summarized the current, desired and ideal capabilities for both LEO and GEO.

Table 1. Current and desired capabilities for LEO and GEO

Characteristic	Current capabilities	Desired (good)	Desired (excellent/ideal)
False Alerts	>99% false alerts	< 10%	< 1%
Total Alerts Raised	>50 Alerts per month	<2 Alerts Per Annum	<1 Alert Per Annum
Acceptable Collision Probability Level	1x10 ⁻⁵	1x10 ⁻⁴ when also combined with improved data and alert reduction	1x10 ⁻² when also combined with improved data and alert reduction
Size of Object (LEO)	LEO 10 cm (1cm LEOlabs TBC)	LEO < 1cm	LEO < 1cm
Size of Object (GEO)	GEO 100 cm (35 cm EU-SST)	GEO < 20cm (good),	< 10cm (excellent), < 1cm (ideal)
48 hour Prediction accuracy	48 hour prediction Along-Track Accuracy +/- 2km Cross-Track Accuracy +/- 0.5km Radial Accuracy +/- 0.5km	48 hour prediction (excellent) Along-Track Accuracy +/- 0.3 - 1km Cross-Track Accuracy +/- 0.2 - 0.4km Radial Accuracy +/- 0.1km	48 hour prediction (ideal) Along-Track Accuracy +/- 0.2km Cross-Track Accuracy +/- 0.08km Radial Accuracy +/- 0.02km

2.2. Object characterization

The alarming recent increase in the population of satellites and space debris in Earth orbit has caused overcrowding in highly desirable operating regions. Governmental cataloguing, analysis and alarm systems are becoming overwhelmed and inadequate to manage the current condition. It appears that operations taking place in orbit, which are currently safe, may be at risk.

Space Traffic Management (STM) has two main objectives: to improve the knowledge of behaviour, the cataloguing and monitoring of space debris, and to improve the prevention of collisions in orbit. In this way it is also possible to obtain greater safety for manoeuvres at close range and to increase the reliability of alarms for collision events. As the different orbital bands become increasingly more crowded, and the number of objects passing from one band to another consequently increases, the ability to successfully predict potential

collisions and to take action to avoid them is essential. Predicting these events requires adequate data, advanced algorithms, identification and tracking techniques.

An effective remediation measure in order to stabilize the population in Low Earth Orbit (LEO) include the active removal of large, massive space debris and collision avoidance by deviating the objects using, e.g., ground-based lasers. Both techniques require not only precise knowledge of the target objects' orbits, but also of their attitude because, to accurately propagate the orbits of potential collision partners, non-conservative orbital perturbations, such as the pressure of solar radiation and atmospheric resistance, which depend on the attitude, must be known. The state of the object, which traditionally consists of position and speed, is certainly of interest, but additional information are also crucial.

In astronomical imaging, the aperture photometry technique is commonly used to estimate the position and luminosity of objects within an image [14]. This technique involves selecting a small circular area, called an aperture, centered on the object of interest. The total amount of light within this aperture is then measured and used to determine the object's luminosity. One important aspect of aperture photometry is the estimation of the object's centroid, or center of mass pixel coordinate. This is typically done using sub-pixel precision algorithms that take into account the distribution of light within the aperture. The centroid of the object is represented as a green point in the images shown in Figure 5.

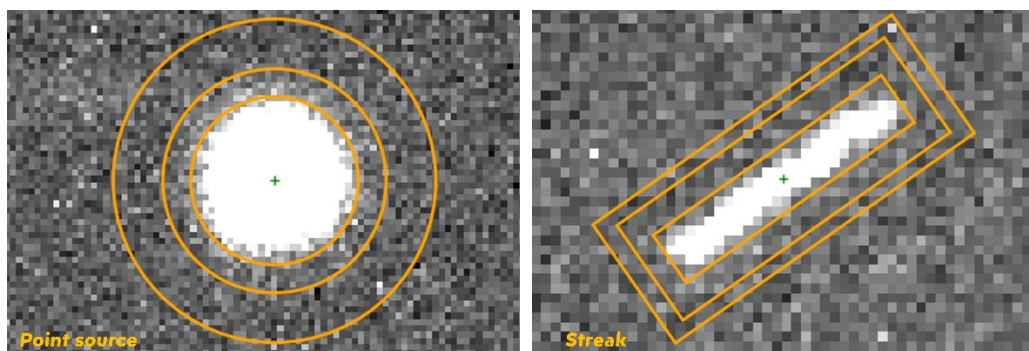


Figure 5. Aperture photometry

Characterization of space objects involves determining various attributes that define their behaviour and physical properties. This includes details about their attitude motion, shape, material composition, and other physical features. The state of an object, typically defined by its position and velocity, is complemented by this additional characterization data to improve understanding and prediction capabilities. Observations provide crucial insights into object stability, rotational frequency, and any manoeuvres performed, all of which can indicate the object's status and potential risks it may pose to active operations. In Figure 6 a representation of the main information that can be useful to know of a RSO.



Figure 6. Object characterization

Using optical data, it is possible to identify several features of space objects, such as their type (e.g., debris, operational satellite, or rocket body), basic positional information, and physical characteristics like visual magnitude and size. By analysing these attributes, operators can distinguish between functional satellites, defunct spacecraft, and debris. Patterns in observed brightness over time can also reveal rotation rates and stability, offering insights into the object's current state and operational history. Optical data is thus a fundamental

tool for both the characterization and ongoing monitoring of objects in increasingly congested orbital environments.

2.3. Challenges in frame analysis

Automatic frame analysis of astronomical images containing satellites presents several complexities. These arise from different factors, that can be the behaviour of the objects, the geometry of the acquisition, the quality of the frames, the image sensor used for the acquisition and the optics of the observatory. Some relevant examples are analysed in the following bullet list.

- **Tumbling and flashing objects:** These objects can cause irregular and unpredictable light patterns that, in sidereal tracking, result in discontinuous traces. This makes it difficult for segmentation algorithms to extract the complete trace. Additionally, determining the start and end points of the trace is challenging because the exposure may have begun or ended when the object was not visible. In object tracking, the object may disappear for several frames, complicating optical tracking and making it difficult to maintain a consistent lock on the object's position.
- **Faint objects:** The detection of faint objects is difficult due to their low brightness, often being close to the noise level of the images, which makes distinguishing them from background noise a significant challenge. The low brightness of these objects can be attributed to various factors such as high phase angles, small size, colours, materials, and their attitude orientation with respect to the observer.
- **Multiple close objects:** Multiple objects that are close together further complicate the analysis, as they can overlap or merge in the images, making it hard to accurately identify and track individual satellites.
- **Frame quality:** Another issue is the lack of prior knowledge about the image conditions. For instance, the presence of clouds or wind can significantly degrade

image quality, introducing variability that automatic systems must be able to account for without any pre-existing data on these conditions. Furthermore, there's always the possibility that an image is blurred due to tracking errors, where the telescope's movement does not perfectly match the movement of the sky. This blurring can make it difficult to accurately measure the position and motion of objects in the image.

- Other celestial objects: One issue is that galaxies can sometimes appear as objects, complicating the identification and classification process. Additionally, bright stars and the Moon can cause significant illumination problems in the images, leading to overexposed areas that obscure other details.
- Camera artifacts: Blooming, smearing, and amp glow also pose difficulties, as they can introduce false signals or distortions that interfere with accurate detection and measurement.
- Focusing and collimation: Problems with focusing and collimation can result in blurry or distorted images, making it harder to discern fine details. Furthermore, field distortion can warp the image, affecting the accurate positioning and shape of observed objects.

All these factors contribute to the complexity of developing reliable automatic image analysis systems for astronomical observations involving satellites. Some examples of challenging frames to analyse are shown in Figure 7.

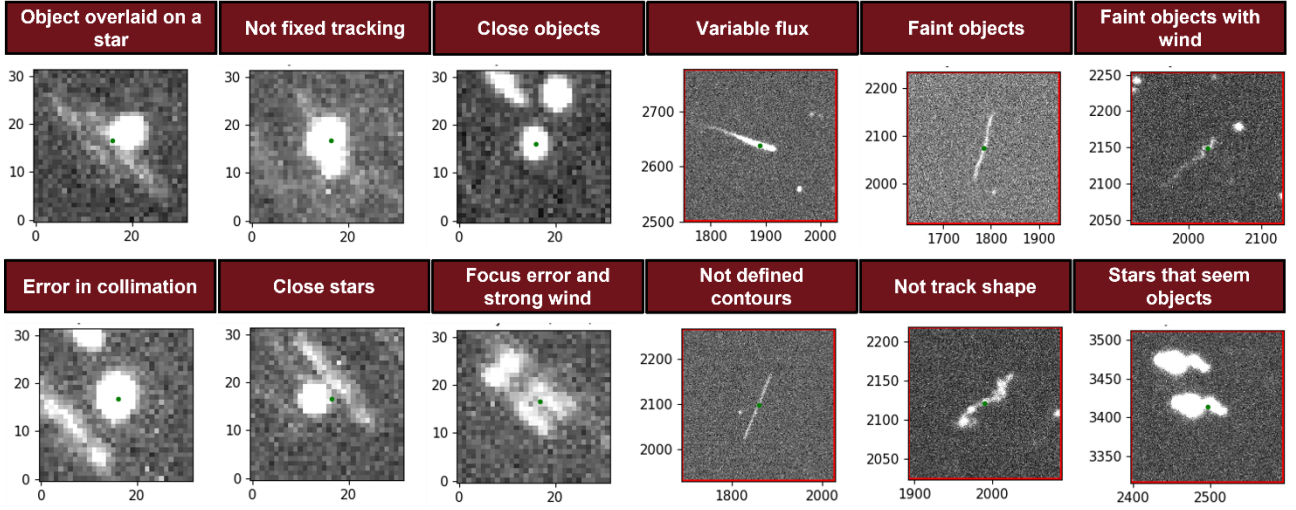


Figure 7. Example of various source of errors in object detection

2.4. Methodologies and techniques used in SSA/SST

Space Situational Awareness (SSA) and Space Surveillance and Tracking (SST) are crucial research areas for monitoring the increasing population of satellites and orbital debris around the Earth. However, the literature on photometric and astrometric applications specific to artificial objects in space remains limited, with few standardized methods compared to traditional astronomy. Despite the growing demand for advanced SSA/SST solutions, automating the processes of object recognition and photometric measurement in space imaging remains challenging due to the dynamic characteristics of orbiting objects and the complexity of capturing high-quality astronomical images under variable observational conditions.

Historically, photometric analysis in SSA/SST relied heavily on manual processing, with operators frequently using software that enabled the manual drawing of aperture circles around light sources (such as satellites and debris). This process allowed operators to isolate the target object's light from background noise for precise photometric measurements. Although modern methods have increasingly shifted toward automated approaches, manually-drawn apertures are still valuable when analysing crowded fields, low-brightness

objects, or variable sources. In such cases, the complexity of the star field and stray light effects often necessitate manual intervention to ensure photometric accuracy, as fully automating aperture photometry for these specific conditions is still a considerable technical challenge.

To support these photometric tasks, several software packages initially developed for crowded-field stellar photometry have been adapted for SSA/SST applications. DAOPHOT (Dominion Astrophysical Observatory Photometry), a software suite designed for measuring point sources in densely populated fields, is particularly notable. Originally used in stellar photometry, DAOPHOT has demonstrated strong capabilities for identifying and measuring point sources in high-density fields, including satellites and space debris [15]. Another widely used tool is SExtractor (Source Extractor), which was developed for the identification and measurement of multiple sources in astronomical images [16]. SExtractor's segmentation and automatic classification capabilities make it a versatile tool for detecting and performing photometry on faint objects, especially within large fields of view where manual identification would be time-intensive and resource-prohibitive.

Additional tools, such as Astrometry.net [17] and SCAMP [18], provide further advancements in astrometric and photometric calibration relevant to SSA/SST. Astrometry.net allows for automated astrometric calibration even for images without preliminary positional information, while SCAMP is a precision photometry and astrometry calibration tool that supports automatic alignment across multiple images, aiding in the efficient management of large datasets. Although effective in general scientific contexts, these tools often require modifications or supplementary manual intervention for SSA/SST applications, where observational conditions and object motion introduce significant noise and variability.

In parallel, recent developments in artificial intelligence and machine learning are opening new possibilities for the automation of object identification and tracking in space imaging.

Convolutional neural networks (CNNs) and other deep learning models are being explored to classify and detect objects within images, supporting the accurate extraction of information such as position and brightness. Nevertheless, the adoption of these technologies in SSA/SST is still in its nascent stages, with further research and optimization required to adapt them specifically for space surveillance tasks.

Despite these advancements, aperture photometry and object identification in SSA/SST remain complex and only partially automated. The variability and complexity of data collected, coupled with the challenges of photometric calibration under conditions of significant ambient interference, often still necessitate manual analysis to ensure result precision and reliability. Consequently, there is a need for further research in computational techniques to achieve fully automated processes and minimize the need for human intervention.

3. Description of the optical systems

The three systems utilized for data collection include two telescopes, SCUDO and AWARE, and a digital camera system, Mini-SURGE. Mini-SURGE and AWARE are located in Western Australia, while SCUDO is based in Italy. Both telescopes are equipped with cameras from the same manufacturer, Andor, yet differ in their optical tube assemblies. Specifically, SCUDO employs a Newtonian optical tube, known for its cost-effectiveness, whereas AWARE features a more advanced and costly Ritchey-Chrétien design. This combination of systems with varied sensors and optical configurations enables a robust analysis across diverse observational conditions. Table 2 provides a summary of the key characteristics of these three systems.

Table 2. Comparison of the main characteristics of Mini-SURGE, SCUDO and AWARE observatories

		Mini-SURGE	SCUDO		AWARE	
Sensor	Type	CMOS	sCMOS	sCMOS	sCMOS	sCMOS
	Resolution (Mpx)	20.2	4.2			
	Pixel Size (μm)	6.54	11		12	11
Body	Focal Length (mm)	135	1200	750	3974	560
	Aperture (mm)	72			610	200
	Mount Type	Fixed	Equatorial		Alt-Azimuthal	
System	FoV Size ($\text{deg} \times \text{deg}$)	10.0×15.1	1.08×1.08	1.08×1.08	0.71×0.71	2.37×2.37
	Pixel Scale (arcsec/px)	10	1.89		0.67	4.16

The choice of CMOS sensors over CCDs in modern astronomical imaging is primarily driven by the need for higher frame rates, as well as faster exposure and download times. These characteristics are essential today, as the rapid acquisition of large amounts of data is crucial for tracking fast-moving objects and conducting high-frequency observations. CMOS sensors are capable of high frame rates because they integrate readout electronics within each pixel, enabling parallel processing that significantly reduces the readout time compared to CCDs, which transfer charge across the entire sensor to a single readout point.

Moreover, CMOS sensors differ from CCDs in terms of pixel gain structure, as shown in Figure 8. In CMOS technology, each pixel has its own amplifier, which allows for adjustable gain and enhanced flexibility in capturing images under varying lighting conditions. However, this design introduces a non-uniform gain response across pixels, particularly at low signal-to-noise ratios (SNR), resulting in a non-linear response to light intensity. This non-linearity can affect the consistency of brightness levels in low-light conditions, where CCDs typically maintain a more uniform response due to their single readout amplifier. Although

sCMOS technology is advantageous to CCD technology in a number of ways, it does have some disadvantages:

- Increased temporal and fixed-pattern noise: as each pixel is readout individually more temporal and fixed-pattern noise is introduced. sCMOS sensors have more active readout areas than CCDs, which causes an increase in these noise sources. This can be reduced by careful electronic design and calibration by camera companies.
- Rolling shutter artifacts: sCMOS sensors can use a rolling shutter to acquire images, however if dynamic objects in the image are sufficiently fast enough to move on a similar timescale to the roll of the shutter, distortion effects can be introduced. Staggered readout between top row of the sensor and bottom row can also cause image artifacts and lost information, and significantly increases effective minimum exposure times for some applications.

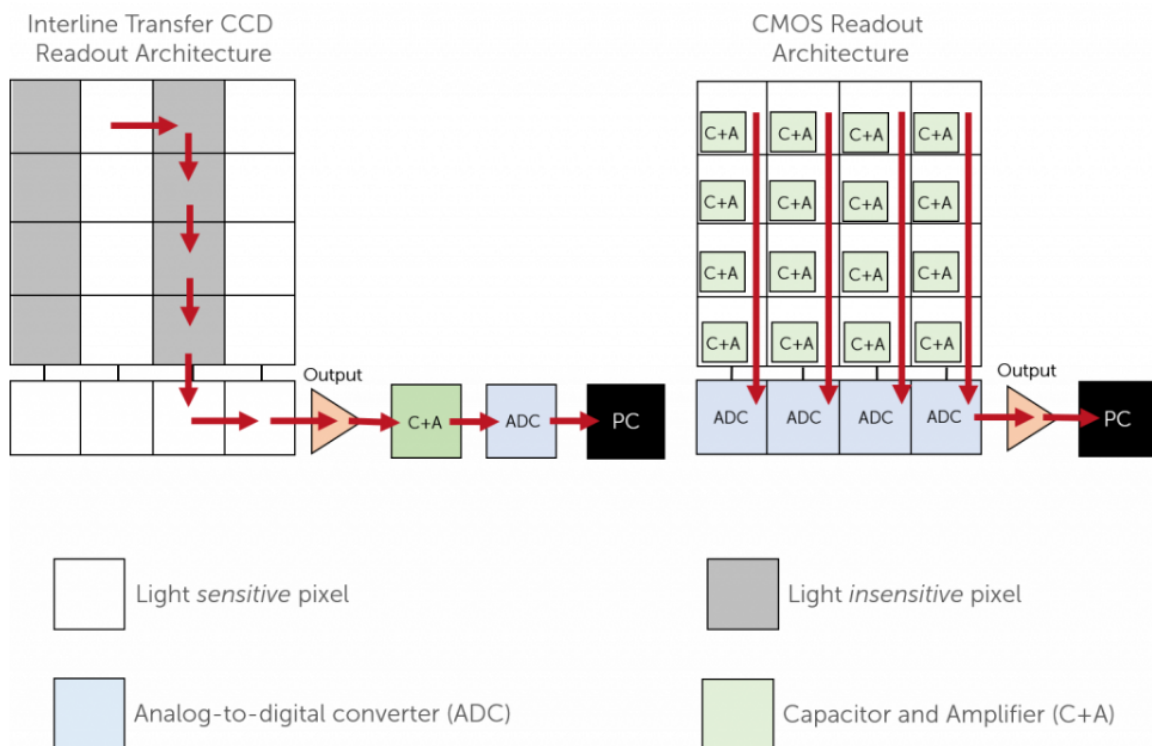


Figure 8. Readout architectures comparing interline transfer CCD and sCMOS sensor. Left: Interline transfer CCD format, in which electrons are shifted off the sensor onto a readout register, output node, amplified (by a capacity (C) and an amplifier (A)) converted into digital grey levels by an ADC. This is then sent to the computer. Right: Typical CMOS format, where every pixel has a capacitor and amplifier associated.[19]

This means that photons that hit each pixel produce electrons, which are converted to readable voltage on the pixel. Voltages from the whole column are sent to an ADC (in which there is one per column), and these are sent straight to the computer. This makes CMOS cameras much faster as they work in parallel [19],[20].

3.1. AWARE

In September 2022, the personnel in the Space Safety Program together with a crew from Baader Planetarium GmbH established and installed a passive optical SST station named Automated Western Australia Reconnaissance tElescope (AWARE). The station is located at latitude -29.046164 NORTH and longitude 115.345184 EAST in Western Australia (Figure 9) on the Western Australia Space Center (WASC), a site owned, operated and maintained by SSC's Australia-based company SSC Space Australia Pty Ltd.

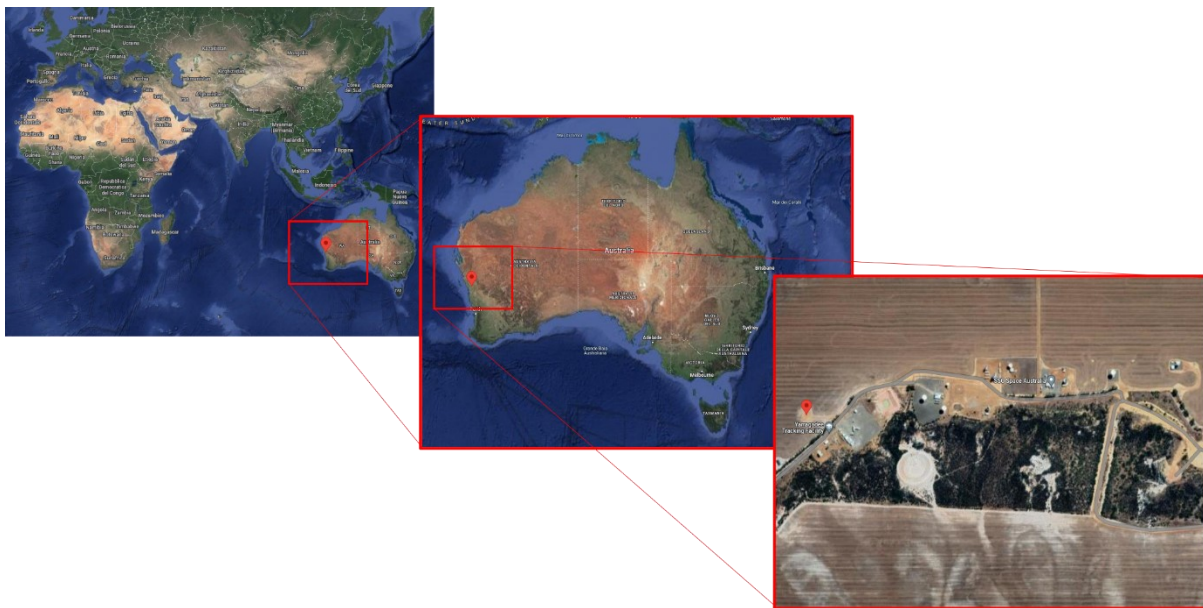


Figure 9. AWARE location

The site is manned by a staff of five people with relevant expertise and experience in facilitating and supporting long-term operations of ground station antennas and equipment. All necessary tools, machinery and equipment are available on site to carry out maintenance

and certain repair tasks should that be required. The station includes a telescope and camera pair in twin configuration that consists of two telescopes, two cameras, two filter wheels, focusers, and a rotator attached to a high-speed tracking direct drive mount as well as auxiliary equipment such as heaters, an air conditioning unit, emergency weather station, additional power supply and a security webcam (Figure 10).

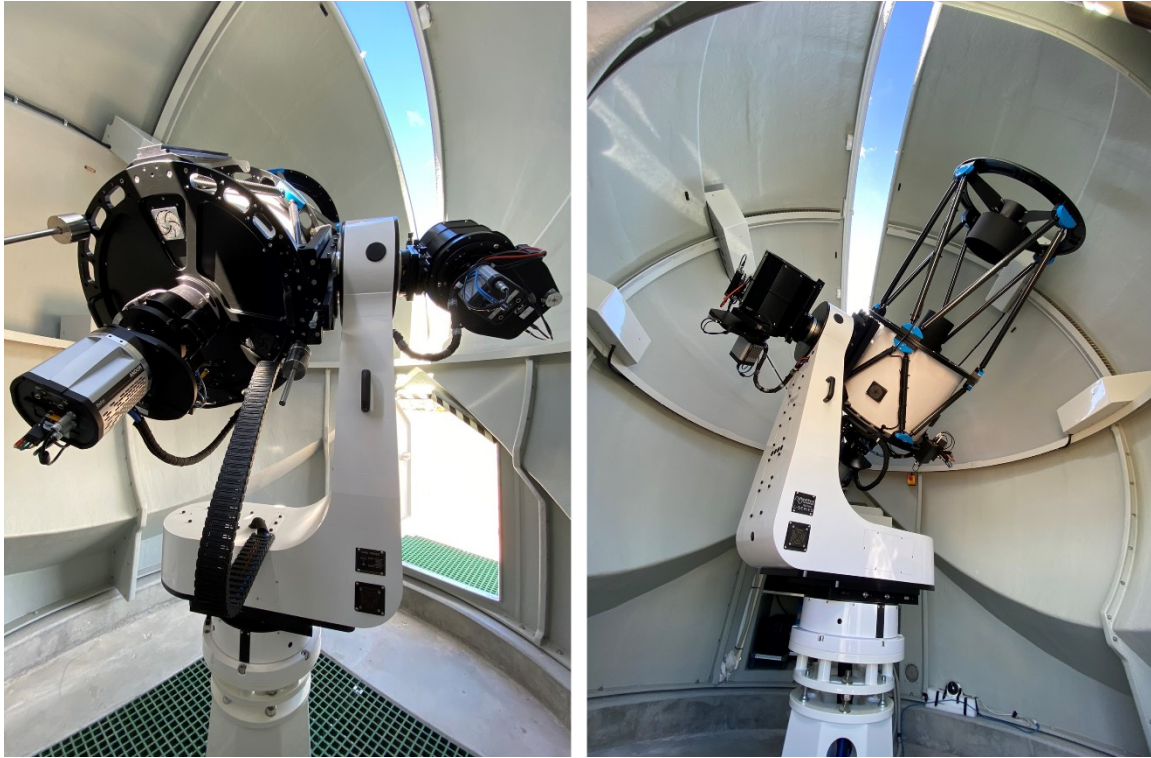


Figure 10. AWARE optical configuration

The optical system is protected under a 3.5 m AllSky/Clamshell dome that is in turn placed on top of a concrete structure. The structure houses a racked server computer, a GNSS time server and Signal Distribution Unit, a switch, spare parts, maintenance equipment and tools. Both the dome and shelter are accessible from the outside through separate locked doors. Figure 11 shows the high-level system architecture of the AWARE station.

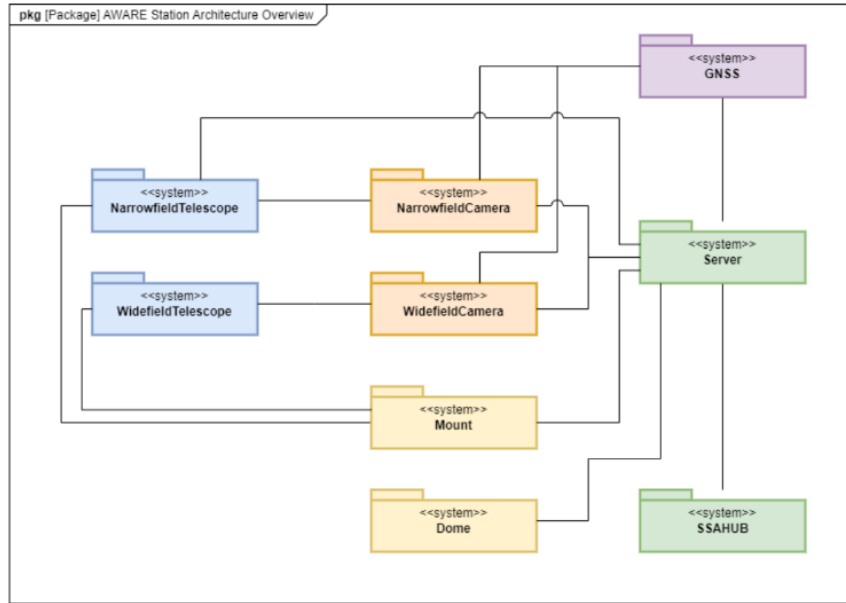


Figure 11. AWARE station architecture

The server computer located in the shelter at the AWARE station has multiple terabytes of storage and powerful processing capabilities with two 8-core Intel processors and an Nvidia Tesla T4 16GB GPU. It enables multi-threaded processing of large amounts of raw data locally on-site, removing the need to transfer large volumes of data to a centralized processing unit. Automated protocols and routines are set up to immediately process, analyze and transfer data once it becomes available (i.e., after successful acquisition), to a data storage in Sweden.

Table 3 describes the technical specifications of the two telescope and camera pairs installed in the station. The narrow field setup is significantly more sensitive than the widefield setup but has a smaller Field-of-View (FOV) and is therefore the preferred setup for observations requiring higher degree of accuracy.

Table 3. AWARE main optical characteristics

Telescope/camera-pair	Narrowfield	Widefield
Telescope model	PlaneWave CDK24 OTA	PlaneWave DeltaRho 200 OTA
Camera model	Andor Balor sCMOS	Andor Marana-11 sCMOS
Primary aperture diameter [mm]	610 mm	200 mm
Focal length [mm]	3 974 mm	560 mm
Field size [mm] (diagonal)	70 mm	32 mm
Sensor chip size [mm]	50 x 50 mm	22.5 x 22.5 mm
Pixel size [μm]	12 μm	11 μm
Frame rate	Up to 54 fps full frame	Up to 74 fps full frame
Readout [ms]	18.5 ms	< 50 ms
Readout modes	Rolling & global shutter	Rolling shutter
FOV [$^{\circ}$]	0.71 $^{\circ}$ x 0.71 $^{\circ}$	2.37 $^{\circ}$ x 2.37 $^{\circ}$
Resolution ["/ px]	0.67" / px	4.16" / px
Limiting magnitude	~17.7	~14

Both telescope and camera pairs are attached in twin configuration on the same mount and are aligned to have coinciding central points in the respective FoVs. The mount is a direct drive high-speed tracking L-600 model from PlaneWave installed in an Alt/Az configuration with maximum slew speeds of up to 50 $^{\circ}$ / second. The dual telescope configuration improves the system flexibility by allowing the station to select data from the higher quality source for the given operational needs. Some examples include the use of the narrow field for detecting dim GEO objects with high precision, or alternatively using the widefield for fast moving LEO or surveying large sectors of the sky. Each telescope is equipped with a filter wheel with a set of photometric filters for each camera. In particular, the wide-field camera uses the UBVRI Johnson-Bessel filter set, and the narrow-field camera utilizes the SLOAN filter set. The two photometric set are shown in Figure 12.

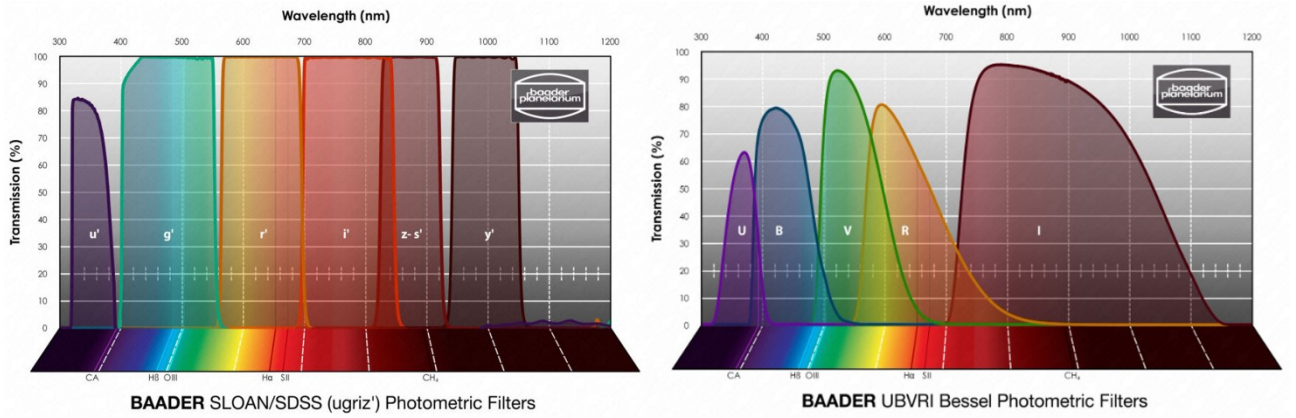


Figure 12. SLOAN (left) and Bessel/Johnson (right) photometric filters used in the AWARE observatory

The dome that protects the telescopes and cameras from the environment is of AllSky or Clamshell design and is manufactured by Baader Planetarium GmbH. The dome has a redundant Uninterruptible Power Supply (UPS) system that will activate in case of primary power failure or outage. Its sole purpose is to close the dome, ensuring that the equipment will remain safe and unharmed from environmental effects like precipitation. The interior of the dome is automatically climate controlled with an A/C unit. The purpose of controlling the dome's temperature is two-fold: to maintain optimal conditions for the camera units and to achieve temperature equilibrium with the outside before opening the dome segments. There is also a security camera installed inside the dome, streaming real-time high-quality video to the control room in Stockholm, Sweden.

3.1.1. Factory Acceptance Test and installation

A series of acceptance tests were conducted across all components and subsystems of the observational setup, including the dome, mount, telescope, sensors, and accessories, to ensure full operational readiness. Each subsystem underwent multiple verification checks, which included inspections (I), demonstration (D), and testing (T). In the dome subsystem, tests confirmed the remote and manual control of the dome, emergency closure protocols, waterproofing, and power compatibility. The mount subsystem tests evaluated mechanical and tracking precision, including sidereal and satellite tracking, high-speed slewing, and direct drive autotuning. The telescope and filter wheel components were tested for proper

alignment, movement range, and operational continuity, with particular attention to the optical tube collimation. The sensor tests for Balor and Marana cameras assessed power cycling, cooling efficiency, framerate stability, noise levels, timestamping, and metadata integrity, ensuring that the imaging equipment met the expected standards. Additionally, accessory checks verified cable length and functionality.

After the FAT, the equipment was packed and shipped to Australia. The equipment was delivered to Australia on the first days of September and the establishments activities began on the mid-September. The setup and installation activities included coordinated tasks performed by Baader Planetarium, SSC, and Sapienza, each contributing to the readiness of key components in preparation for operational deployment. Baader Planetarium's responsibilities included preparing items for lift, lifting instruments, dome installation, and telescope cabling. These activities spanned from September 17 to September 25, 2022, with buffer days included to accommodate any potential delays. SSC undertook the setup of OS and network infrastructures on September 15, followed by a status report and testing phase through September 20. Accessory setup and hardware integration proceeded between September 20 and September 23, followed by the initiation of operations for the AWARE station from September 23 to September 27. Meanwhile, Sapienza installed and configured the Mini-SURGE system. Installation occurred from September 15 to September 18, with configuration and testing extending until September 25, leading up to Mini-SURGE operational readiness on September 26-27. This detailed timeline allowed for systematic preparation and coordination across teams to ensure all systems were functional and synchronized for smooth operation. Figure 13 provides a selection of images showcasing the hardware tested during the FAT, along with members of the AWARE project team and scenes from the observatory installation process. These images illustrate key components, and the collaborative efforts involved in preparing and setting up the observational infrastructure.



Figure 13. Instrumentation and team members for AWARE FAT and installation

3.1.2. Tasking and scheduling

The station is entirely automated and can be remotely operated from SSC headquarters in Stockholm, Sweden. The station is operated by SSC in-house developed monitor & control software and scheduler. It is capable of ingesting observation schedules programmatically through an API or manually with a GUI front-end service. The API of the 3rd-party proprietary software PWI4 is used to control the mount and the cameras are controlled with 3rd party proprietary API. The processing and image frames analysis software was developed under this thesis and the entire software architecture is containerized, which means that all components are isolated and communicate with each other through well-defined protocols. This also enables the station to reach a higher level of hardware agnosticism.

Figure 14 shows a pair of frames acquired via the AWARE station telescope and camera pairs. On the left the object tracked (highlighted) is a 16U CubeSat in GEO orbit, and above it two drifting GSO objects are visible the frame on the right shows a compressed and example from a widefield observation. The object tracked, in this case, is a BeiDou navigation satellite in IGSO. Many other GSO satellites are visible in the top-right of the image, as well as a MEO in the bottom right.

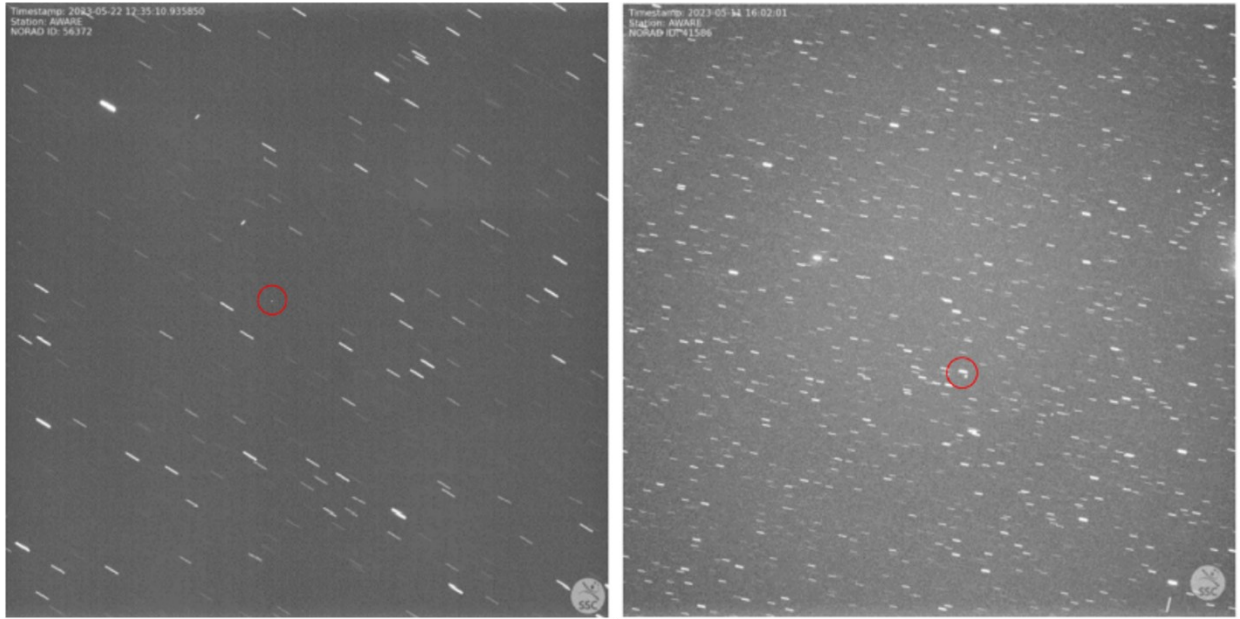


Figure 14. Narrow-field (left) and Wide-field (right) acquisition examples

3.2. Mini-SURGE

Mini-SURGE is an optical observation system with a large FoV designed to perform surveys of GEO orbiting objects. The measures obtained from those images provide key information, such as celestial coordinates and luminous fluxes in the RGB bands, of the visible satellites and space debris. One of the key features of the observatory is that the core module is small and compact, making it easily scalable and transportable. Mini-SURGE, in fact, is already part of a bigger system, composed of two similar observatories, SURGE and Mini-SURGE, aiming to extend to more branches. Mini-SURGE is placed in the AWARE observatory's North wall pointing in the North direction to view on the GEO ring. The location allows for nearly total absence of the light pollution originated from the cities and the possibility to monitor a completely different portion of the sky with respect to its similar system, located in the opposite hemisphere in Colleparado, Italy. The system's core consists of two cameras equipped with CMOS image sensors, mounted on a wooden support frame featuring a skeleton made of aluminium profiles. The cameras are controlled by a computer housed within the same enclosure as the other system components. The cameras are secured to the frame using adjustable mounts with two degrees of freedom, allowing for precise adjustments in

both azimuth and elevation. Electrical boards, power supply, USB hub, computer, and power strip are organized on an insulated shelf inside a single removable drawer, which facilitates easy access for maintenance. The external frame is constructed with water-resistant wooden panels and features a small glass plate in front of the cameras. The panels are fitted onto a framework made of aluminium Rexroth profiles, providing the system with stability against wind and vibrations. The computer drawer can be easily pulled out through a side door of the structure and a sliding trolley mechanism. Additionally, a roller shutter is integrated into the system to shield the cameras from direct sunlight during the day, and it can be remotely controlled via an electric relay. A qualitative 3D model of Mini-SURGE is depicted in Figure 15.

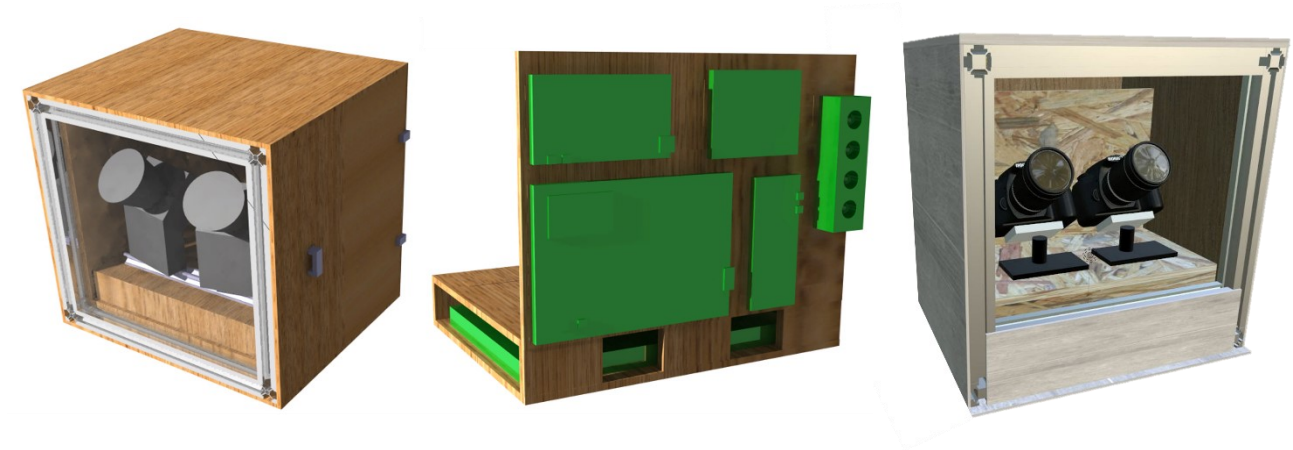


Figure 15. 3D model of Mini-SURGE

The camera system does not have a movable mount like typical telescopes, while it is fixed to the ground. With this setup the observatory constantly watches the same GEO objects, since their orbital period is the same as the Earth's sidereal day. The objects are, therefore, fixed in the FoV and they appear with approximately circular shape in the images. To this aim, the cameras must be inclined at an El of 56° with respect to the local horizontal. In terms of Declination (Dec), on the other hand, the cameras must point to 4.8° as shown in Figure 16.

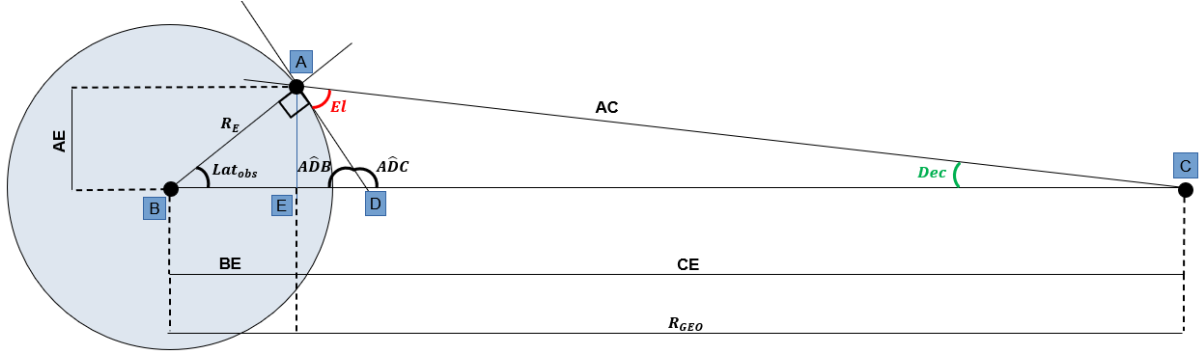


Figure 16. Geometry for GEO acquisition for Mini-SURGE

In Figure 16 are indicated with R_E the Earth radius (6368 km), R_{GEO} the GEO radius (42241 km), Lat_{obs} the observatory latitude (29.083°), El the elevation and Dec the declination to which Mini-SURGE must aim. In Figure 17 Mini-SURGE is shown in its workstation, next to the SSC telescope, which is in the dome.



Figure 17. Observation system: Mini-SURGE

The overall dimensions of Mini-SURGE are 0.5 meters in length, 0.6 meters in width and 0.6 meters in height and globally weighs around 155 kg. The weight is legitimated by the choice of heavy aluminium that ensure the system's stability against the strong wind present in Australia. Every camera is equipped with 135 millimetres focal length, allowing a FoV of 15.4 degrees for 10.2 degrees. The two cameras obtain together a total FoV of 30.8 degrees for 10.2 degrees. Camera's resolution is 5472 pixels for 3648 pixels and the pixel scale is 10.1

arcseconds/pixels. Pixel size is 6.55 micron and sensor size is 35.8 millimetres and 23.9 millimetres in height. The main features of the observatory are summarised in Table 4.

Table 4. Main Mini-SURGE characteristics

GENERAL	DIMENSIONS: l[m]xw[m]xh[m]	WEIGHT [kg]	FOV SINGLE CAMERA	TOTAL FOV	
	0.5 x 0.6 x 0.6	154.399	15.4 x 10.2	30.8 x 10.2	
OPTICS	RESOLUTION [pxxpx]	FOCAL LENGTH [mm]	PIXEL SCALE [arcsec/px]	SENSOR [mm]	PIXEL SIZE [um]
	5472 x 3648	135	10.1	35.8 x 23.9	6.55

Since 2021, Sapienza University of Rome has a collaboration agreement with the SSC for the activities of SSA. The Mini-SURGE project, started in 2022, fits within this agreement and was installed in Australia within a mission coupled with the installation of AWARE. Mini-SURGE is positioned next to the AWARE telescope, with the objective of working as a support for the observation strategy of the latter, reducing the time for the observation of all the targets in a portion of the GEO ring, as well as to identify new targets in the GEO belt. Thanks to its large FoV, Mini-SURGE can observe dozens of objects simultaneously, providing a concurrent survey of all of them.

3.2.1. Preliminary test and installation

The Mini-SURGE installation in Australia was scheduled for 2022, September, 27th. A test campaign was carried out to verify its functionality after being completely developed and assembled. The system was previously assembled in Sapienza in 2022, September, 6th and it was tested for one night observation to verify that the complete system worked correctly (Figure 18). The test procedure aimed to demonstrate the remote control of the system, the cameras activities and their response to the commands, the GPS synchronization with the shooting and the images saving. After verification of its functionality through the planned tests, the system was disassembled and packed to get ready for intercontinental transport.

It was transported to Australia in 2022, September, 13th-14th and re-assembled in the observation site's laboratory.



Figure 18. Mini-SURGE tests at Sapienza

During the assembly in situ, each mechanical and electronic part has been tested. For the electronic components, it was verified that both power and control electrical boards received the correct values of voltage and current. After that, voltage and current tests were performed on the electrical components that required a precise voltage value to work nominally, for example cameras power supply. The preliminary test phase also included checking proper response of the roller shutter to the input given through its dedicated program on the computer. This step consisted of verification of the correct opening and closing of the shutter, and checking the pre-set open configuration did not interfere with the field of view of both cameras.

After the complete assembly the system was placed on a damper on the platform and fixed to it through tensioning straps to prevent it from being yanked out from strong winds. Figure 19 shows some pictures of the system installed in its basement at WASC.



Figure 19. Mini-SURGE open (left) and closed (right)

Once the system was ready on its designated position, further tests were performed, aimed to orient cameras according to the design and check that their FoV matched as much as possible with the theoretical FoV (black rectangles) conceived during the project phase (Figure 21). The difference between the theoretical and the real FoV (yellow rectangles) is due to the nature of the structure, which does not allow the precise alignment of the cameras with their theoretical orientations. Nevertheless, the orientation results were successful, since they allowed a total FoV of $26.5^{\circ} \times 10.2^{\circ}$, with a total loss of about 4.3° in Az. This FoV was sufficient to see the main expected targets, such as calibration satellites and a fulfilling number of GEO objects. In Figure 21 GEO satellites are plotted considering a reference time, to point out the orientation of Mini-SURGE towards the geostationary ring, which is the primary target identified for the system. In Figure 20 are shown the geostationary satellites in the Mini-SURGE's FoV. The designed FoV permits to observe at least one SP3 satellite for camera, and it is essential because they allow to pursue an observation campaign aimed to calibrate the acquired measures.

SATELLITES	SSN	SATELLITES	SSN
WESTAR_5	13269	FENGYUN_2F	38049
PALAPA_B1	14134	ASIASAT_6	40141
BRAZILSAT_1	15561	SES_9	41380
OPTUS_A1_(AUSSAT_1)	15993	BD-2-G7	41586
GOES_7	17561	JCSAT_15	41903
IPSTAR_1	28786	TELKOM_3S	41944
KOREASAT_5	29349	CHINASAT_16	42662
CHINASAT_6B	31800	KOREASAT_7	42691
BSAT-3A	32019	BSAT-4A	42951
SES_7_(PROTOSTAR_2)	34941	KOREASAT_5A	42984
BSAT-3B	37207	BANGABANDHUSAT-1	43463
CHINASAT_20A	37234	BEIDOU_IGSO-7	43539
KOREASAT_6	37265	TELKOM-4	43587
CHINASAT_10	37677	TJS-5	44978
BSAT-3C	37776	BEIDOU_3_G3	45807
GAOFEN_13	46610	KOREASAT_116	45920
WFOV_(USA_332)	52940	BSAT-4B	46112
BD-2-G7	41586		
BEIDOU_3_G3	45807		
BEIDOU_IGSO-7	43539		

SATELLITES	SSN	SATELLITES	SSN
WESTAR_5	13269	ASIASAT_6	40141
MORELOS_2	16274	LAOSAT_1	41034
TVSAT_2	20168	QZS-3	42917
GORIZONT_26	22041	ASIASAT_9	42942
HELLAS-SAT_1_(DFS_3)	22175	COSMOS_2526	43432
IPSTAR_1	28786	BANGABANDHUSAT-1	43463
JCSAT_10	29272	GEO-KOMPSAT-2A	43823
COMS_1	36744	GEO-KOMPSAT-2B	45246
JCSAT_13	38331	TIANTONG-1_2	46916
WFOV_(USA_332)	52940	CHINASAT_6D	52255
QZS-3	42917		

Figure 20. Geostationary satellites from NORAD: 34 satellites in the FoV of camera A, 20 satellites in the FoV of camera B and Geostationary satellites for the calibration: 3 satellites in the FoV of camera A, 1 satellite in the FoV of camera B

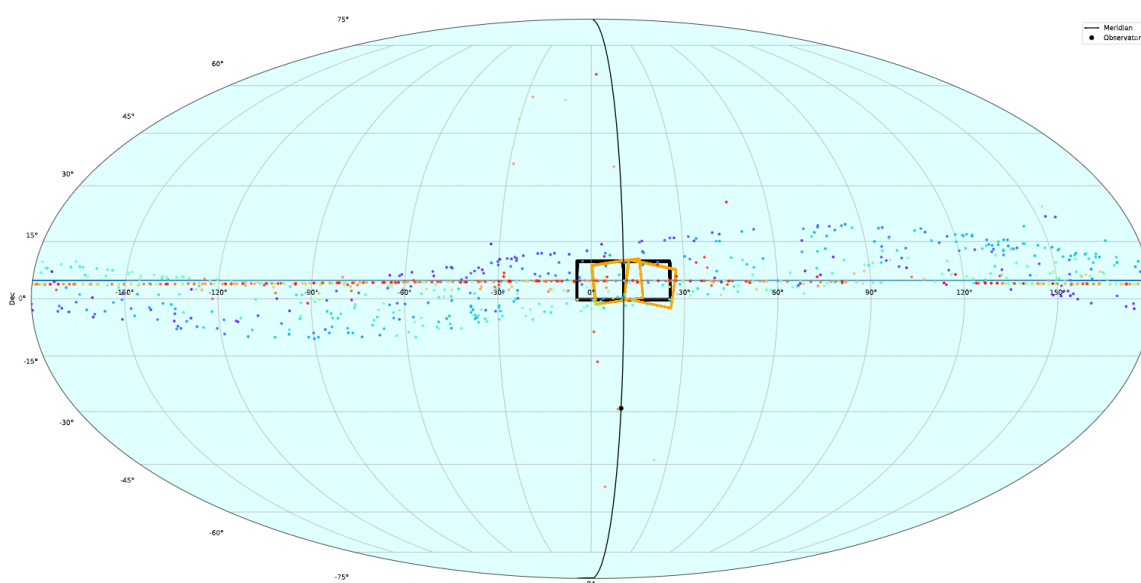


Figure 21. Mini-SURGE FoV designed (black) and real (yellow)

The last test performed in situ was the correct running of a complete observation. The test consisted in checking the internet connection of the system, verifying its ability to be reached through remote control, and the working of the program for automatized observation. The system carries out the observation autonomously, following the instructions written in a schedule file. The latter contains information on acquisition scheduled time and acquisition parameters for every image. After passing the function test, at the end of September 2022,

the system was ready for use and was controlled remotely from the S5Lab station in Sapienza.

3.2.2. Tasking and scheduling

Operation of Mini-SURGE is possible thanks to a software suite, already working on SURGE and readapted for Mini-SURGE during the design process. The control of the observatory is managed by a control software developed in MATLAB [21] equipped with a Graphical Unit Interface (GUI) shown in Figure 22. This allows the external user to directly interact with manual operation such as switching on and switching off the cameras, acquiring single frames or connecting every device needed for the observation.

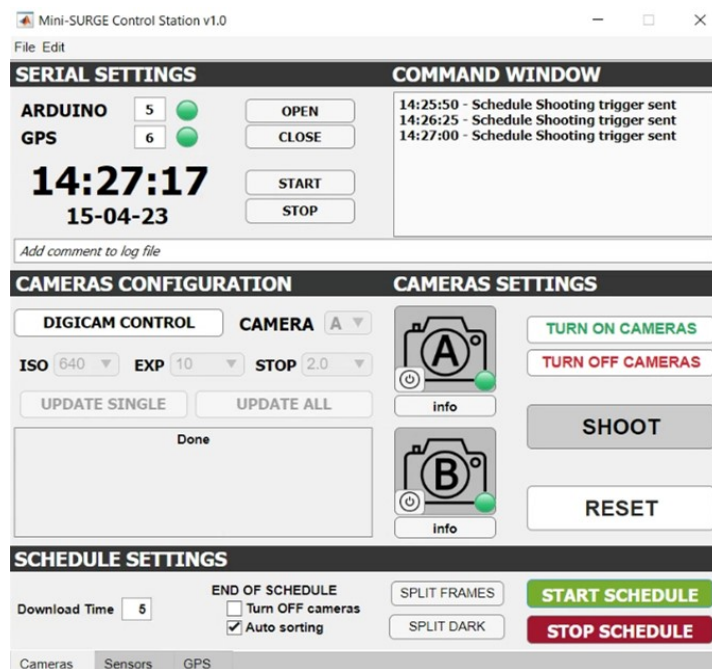


Figure 22. Mini-SURGE control interface

The control software interoperates with other programs which manage different hardware of the system. In particular, the open-source software DigiCamControl [22] handles cameras shooting and images download, while Arduino arms the cameras when requested by the schedule and runs the trigger for cameras after getting the Pulse Per Second signal (PPS) from the Global Positioning System (GPS) receiver. The roller shutter, on the other hand, is

controlled by its own program, which permits to open or close the shutter upon request. Once the schedule starts running, the program reads it and it constantly compares the current time provided by the GPS with the time of the next planned shoot. When times match, the control software questions Arduino for shooting. Arduino immediately asks DigiCamControl to open the cameras' mirrors and then it waits for the PPS signal to effectively send the trigger signal activating the acquisition through DigiCamControl. With this procedure the shooting is always performed at the beginning of the second, so the timestamp is as accurate as the time scanned from GPS. DigiCamControl manages the shoot, following the instructions on acquisition parameters that MATLAB reads from the schedule. After acquisition, the image is loaded and saved on the computer in the preset folder. At the end of the schedule, images from the observation night are saved in a folder with the observation date and divided into subfolders depending on cameras. Hereafter in Figure 23 is shown the concept of operation of Mini-SURGE.

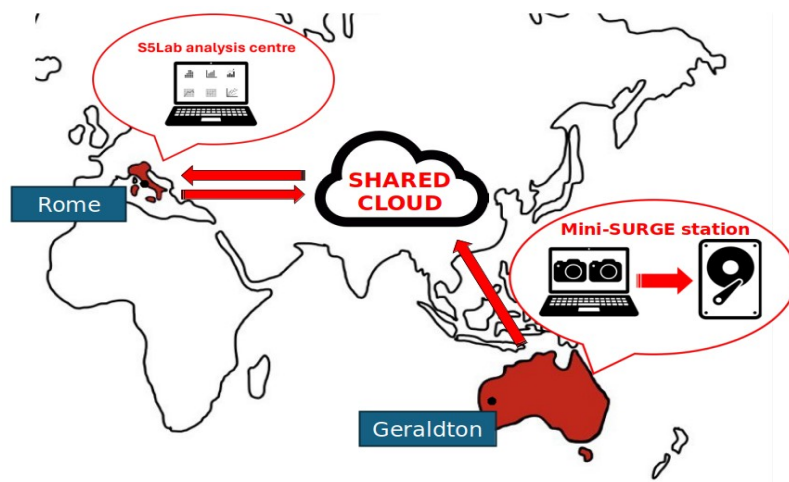


Figure 23. Concept of operation of Mini-SURGE

3.3. SCUDO

The SCUDO observatory is managed by the S5Lab [23] and is positioned within a mountainous region near Rome, specifically in Colleparado (Figure 24). One of the primary advantages of SCUDO's location lies in its distance from major sources of artificial light

pollution, ensuring that the night sky in Colleparado remains relatively unaffected by the glare of urban illumination. Additionally, the observatory altitude, standing at 555 m above sea level, further enhances the quality of the observations by minimizing astronomical seeing. This phenomenon refers to the degradation of the image of an astronomical object caused by atmospheric interference and turbulence. SCUDO observation equipment consists of two Newtonian telescopes: a smaller telescope with a 15 cm diameter and a larger telescope with a 25 cm diameter. The optical tube was paired with a scientific Complementary Metal-Oxide-Semiconductor (sCMOS) sensor. These sensors are known for their high sensitivity and rapid data-acquisition capabilities, making them ideal for capturing detailed astronomical images and data.



Figure 24. SCUDO observatory (Colleparado, Italy) managed by the S5Lab research team.

The system is also equipped with a filter wheel that holds a set of Sloan photometric filters. The transmission curves for each filter are illustrated in Figure 25. Further detailed characteristics of SCUDO are provided in Table 2.

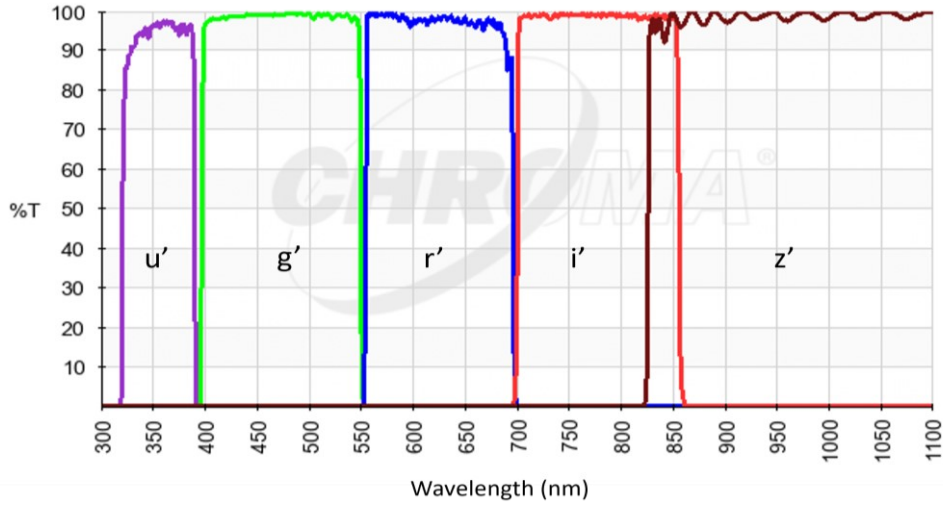


Figure 25. The transmission curves of the Sloan filter set [24] are delineated by different bands. The u' band corresponds to the near ultraviolet region of the electromagnetic spectrum. The g' and r' bands cover the two halves of the visible spectrum. Additionally, the i' and z' bands represent two bands of the near infrared.

4. Software for frame analysis

The collaboration between Sapienza and Swedish Space Corporation (SSC) started in 2021 with a project aimed at developing advanced capabilities for frames analysis, orbit determination, and light curve extraction from space surveillance data. This project involves establishing coordinated observation strategies for monitoring RSOs across various orbital regimes and strengthening collaboration with existing observatory networks. Key objectives also include the development of software tools for precise data extraction and the integration of machine learning techniques to improve data processing efficiency. The software developed through this collaboration has been actively used since 2023 to process data from the AWARE optical station located in Western Australia, owned by SSC. Subsequently, in 2024, the software was utilised for AWARE's qualification and validation campaigns to integrate into the EU SST network. The name of the software is Frame Analysis and Trajectory Evaluation (FATE) is designed to efficiently analyze images produced by an optical observatory (Figure 26). The main goal is to achieve a high degree of automation in image

processing, significantly reducing manual intervention and enhancing the speed of analysis to permit quasi-live analysis.



Figure 26. FATE logo

4.1. Architecture

The raw frames obtained by the optical station are processed immediately after acquisition. If the frames are acquired faster than the processing speed, a new thread is created, and multiple threads can be executed in parallel. In some cases, especially for LEO TDM tracking where a high framerate is desired, processing jobs get queued in a backlog that gets progressively emptied with a FIFO strategy as resources become available. The detailed process for data acquisition is shown in Figure 27.

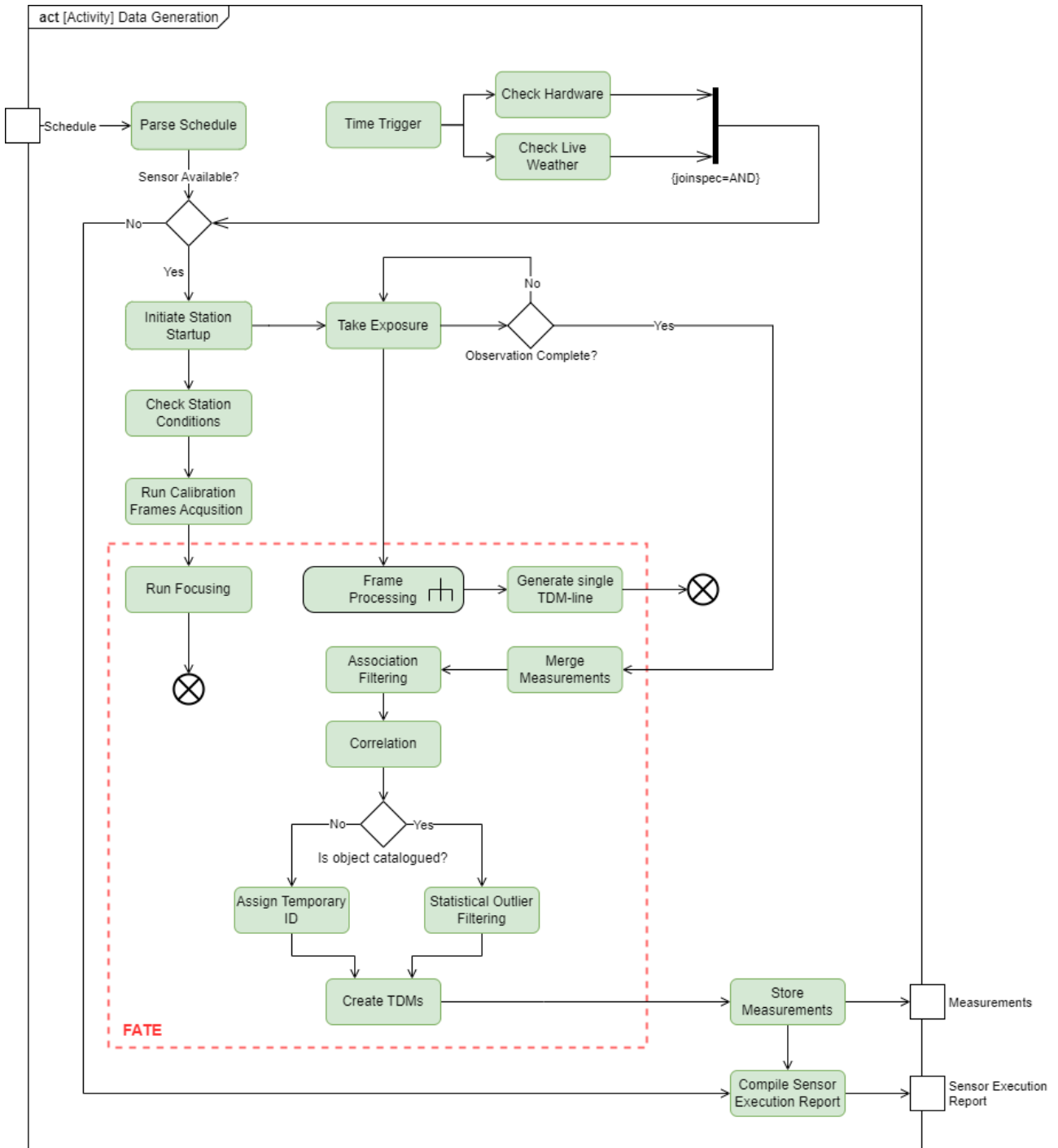


Figure 27. Data acquisition activity diagram

As previously shown in Figure 27, at the end of the processing activity, the set of coordinates corresponding to the processed frame is saved in a temporary file. Each of these files are merged into a single TDM at the end of the object's observation.

In order to connect the measurements to each other throughout the observation, the process of association is used. In the object tracking mode, the association is only done for a single target object, that is assumed to be the closest to the propagated coordinates in the frame. This process will be superseded by integrating the association process into the object recognition software. Once every object in the frame has been distinguished from all the others, the correlation is performed by evaluating the distance between the object extracted coordinates to their propagated positions. Since there is no prior knowledge of the orbits of the non-tracked objects in the FoV, all the available objects in the catalogue are propagated for the duration the observation timeframe, with assumption on the objects' orbit based on the object recognition results.

In the survey mode, the distance between the object and the propagated coordinates are evaluated immediately after detection. If an object cannot be matched to any others in the public catalogue, the measurements are stored in a TDM file with a temporary ID, to be eventually used in orbit determination (OD) or initial orbit determination (IOD) procedures.

Once the correlation is completed, the angular statistical outliers are filtered out and the final TDMs are created, stored, and delivered to the customer, along with the compiled Sensor Execution Report. This data transfer chain allows SSC to back up the data, both on the local server at the AWARE station and the SSA-HUB server in Stockholm. The local analysis parallelization and execution during the observation enables very low processing and transfer latencies. The same processing technique is carried out in parallel for both cameras, and they will both generate independent TDMs.

A further activity envisioned for the proposed solution is a quality evaluation block that will assess which of the two TDMs is more appropriate for the selected target and return only a single result. This method would increase the station reliability, as for every observed object only the best data is released which would be assessed on the actual observation data.

Generally, the widefield telescope is more suitable for LEO tracking, due to the higher numbers of stars in the background, as well as for GEO surveying. The narrow field is better suited for MEO and GEO tracking, due to the larger light gathering capability and better angular and sensor resolution.

4.2. APIs and GUI

Application Programming Interfaces (APIs) of a software are a set of interfaces, protocols, and tools that allow other software to interact with it. APIs provide methods and functions that can be invoked by other programs to perform specific operations. These operations can include data access, command execution, and more. APIs serve to hide the internal complexity of the software and expose a simple interface for integration. The main FATE APIs are reported in Figure 28 where are also highlighted the relationship between them.

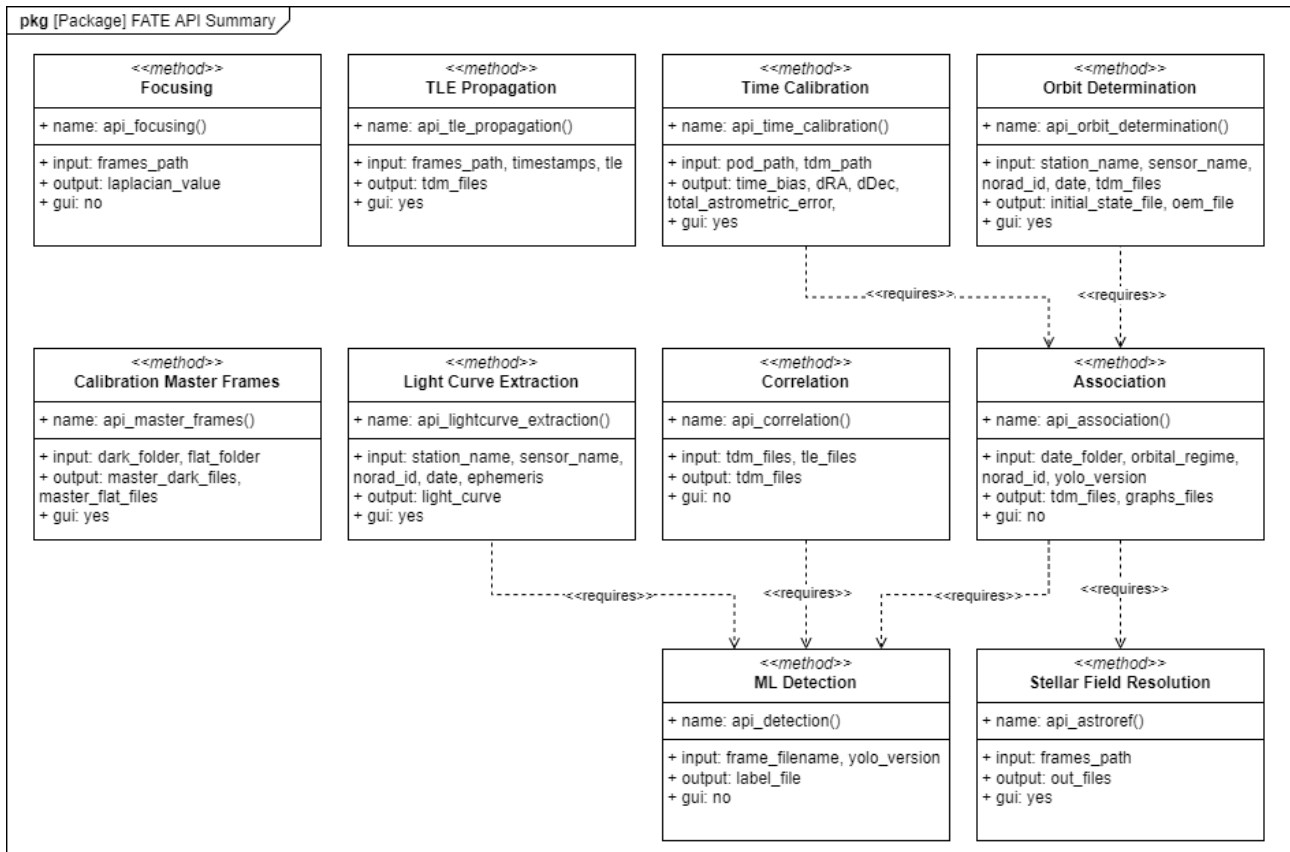


Figure 28. FATE API

The Graphical User Interface (GUI) of the software provides a user-friendly, visual interface for interacting with the application. It allows users to perform various tasks through graphical elements such as buttons, menus, and dialogs, rather than through text-based commands. The GUI is designed to be intuitive and easy to navigate, enabling users to access and manage the software's features efficiently. In FATE, the GUI is primarily used for testing purposes, allowing users to manually execute and verify operations (Figure 29). It is also useful when frame analysis is not required during data acquisition, providing a simpler way to interact with the software without the need to process frames in real-time. Additionally, the GUI is beneficial for performing manual operations, offering direct control and immediate feedback on the tasks being executed.

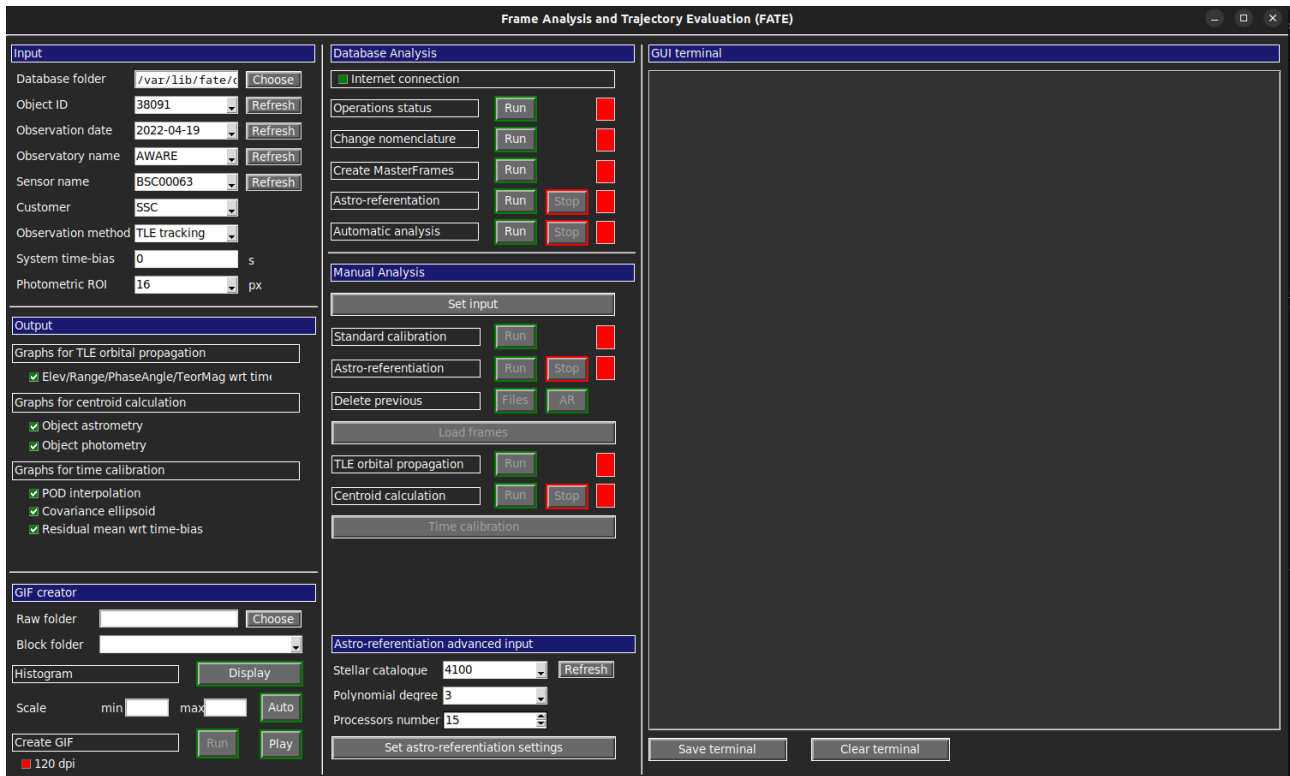


Figure 29. FATE GUI

The GUI is divided into various sections that allow the user to execute specific APIs. The first section to interact with is the Input section, where necessary parameters for the analysis of a series of frames are selected, such as the NORAD ID of the object, observation date, observatory, etc. This section includes Refresh buttons that enable updating the interface data with the latest data from the database. The Output section, on the other hand, is used only to select the graphs to be displayed during the analysis; however, these graphs are also saved. Another output that can be generated with the interface is GIFs of the passes based on the acquired frames. The Database Analysis section allows performing a series of operations on the entire database under examination. The functions that can be executed include updating the nomenclature of files and folders according to user specifications, creating master frames, resolving the star field, and performing astrometric and photometric analysis on frames where these operations have not yet been executed.

4.3. Software deployment in AWARE station

The FATE software has undergone several deployment iterations throughout its development. FATE is integrated with the other parts of the AWARE software via a dockerized (or compartmentalized in Docker containers). To dockerize the FATE software a Docker file is required. This file contains the list of instructions to install the operative system and the FATE requirements on the server. In these requirements are included the Conda environment with all the Python packages in the correct version to execute FATE properly. This file is available on GitLab, and it is constantly being updated to suit the needs of the software. Currently, FATE is deployed on the AWARE server and can be used both manually and used by other processes on the server. In the future, is expected to rely on an updated GitLab system, that will allow Continuous Integration/Continuous Deployment (CI/CD) to be automated.

The software development started in mid-2021 and reached a sufficient state for the beginning of the initial operation of the AWARE station in 2023. The AWARE establishment was planned to be in April 2022, while it was finally delivered on early October 2022. Consequently, the months between October 2022 and January 2023 were mostly spent working on the initial troubleshooting of the observatory. The first issues encountered include an incorrect timestamp on the header of the frames and the improper collimation of the narrow-field optical tube. The missing timestamp issue prevented the use of FATE on the acquired frames from the AWARE station. In particular, the time is fundamental to retrieve the correct coordinates of the object and to provide a correct TDM file for the station time calibration. Also, the incorrect collimation of the narrow-field telescope, caused FATE to improperly extract the centroid of the object. The correction of these aspects was successfully verified in early 2023. Despite these delays, the software was preliminary tested using frames from the Sapienza observatories before the establishment and via the preliminary joint observation campaign promoted by SAAB Australia and other partners with the AWARE observatory.

The development of the FATE software has continued throughout 2023 and reached a state of maturity sufficient to enable real time data analysis in early 2024. This capability was tested under the commitments arising from the qualification and validation campaign of AWARE with the ESA Expert Center. In order to enable a more automated and robust objects detection, without using TLEs propagation, the neural network centroid analysis has been implemented. FATE was able to conduct several observation campaigns that permit the analysis of observation data to meet the parameters dictated by EU SST.

4.4. Data exchange

The FATE software is designed to provide results that can be easily shared and analyzed by other systems in the SST field. In the case of SSC, registered users can access the data through Azure Authentication, ensuring the security of information during transmission. The customers can request some data product, such as raw frames or light curve, or schedule the observation. In both cases the request is passed at the scheduler that creates tasks to be executed by AWARE station. The results collected are initially stored in a physical database located in Australia, where AWARE station acquires data. Subsequently, the data is cloned and transferred to a duplicate database in Stockholm (SSA-HUB), ensuring redundancy and availability in case of failures or access issues with the primary database. A representative scheme of the data exchange is shown in Figure 30.

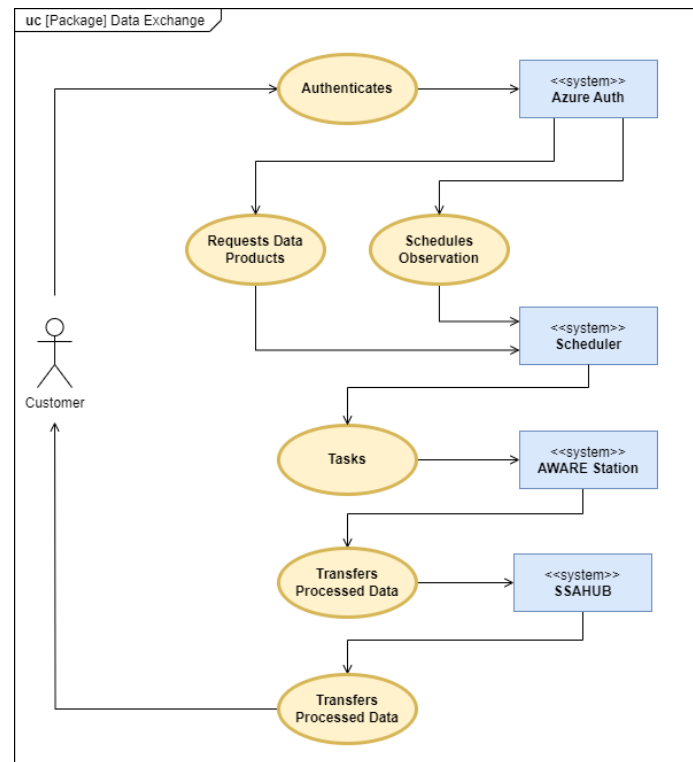


Figure 30. Data transfer

To ensure inter-operability between different station, all the results are saved in standard file formats that are widely used in this field, such as Tracking Data Message (TDM), Precise Orbit Ephemerides (POD), or Two-Line Elements (TLE).

- The TDM format is a standard for exchanging tracking data in the space surveillance community. It contains information about the object's position, velocity, and other relevant parameters, as well as metadata about the observation, such as the time and location. A TDM will be shared in Keyword Notation Value (KVN) format and is realized as a sequence of plain ASCII text lines which may be in either a file format or a real-time stream. The content is separated into three basic types of computer data structure. The TDM format is a three-part structure consisting of a header, metadata and data fields. This structure takes into consideration that different components of tracking data are updated more or less frequently, so that the data field includes those tracking information that can change on a measurement-by-measurement basis, while the metadata and header fields store those that change several times per track (metadata) and once per file (header). The TDM makes it possible to convey a variety

of tracking data used in the orbit determination process in a single data message (e.g., standard Doppler and range radiometric in a variety of tracking modes, VLBI data, antenna pointing angles, etc.). To aid in precision trajectory modelling, additional ancillary information may be included within a TDM if it is desired and/or available (e.g., media corrections, meteorological data, clock data, and other ancillary data), and facilities for documenting comments are provided [24].

- The POD format is used to represent the trajectory of a space object with high accuracy, taking into account the effects of various gravitational and non-gravitational forces. It contains information about the object's position and velocity at different times, as well as information about the uncertainties in these estimates.
- The position and velocity data of satellites are commonly shared using standardized formats such as the Orbit Ephemeris Message (OEM) and the SP3 format. The OEM, developed under the standards of the Consultative Committee for Space Data Systems (CCSDS), provides a comprehensive representation of an object's orbit by specifying state vectors (position and velocity) at given epochs. This format is particularly flexible, accommodating data for a wide range of missions and providing detailed metadata about the coordinate system, time system, and interpolation methods. On the other hand, the SP3 format, originally designed for GPS applications, has become widely used for precise orbit determination across various satellite missions. It offers high-precision position and clock information, typically for multiple satellites.
- The TLE format is a widely used standard for representing the orbital elements of space objects. It contains information about the object's orbit, such as its inclination, eccentricity, and semi-major axis, as well as other parameters that describe the orbit's shape and orientation. By saving the results in these standard file formats, the software ensures that its output can be easily integrated with other systems and used for a variety of applications, including satellite tracking, space debris monitoring, and collision avoidance.

4.5. Database

Like most observatories of its kind, AWARE, SCUDO and Mini-SURGE generates vast amounts of data from the thousands of frames acquired each night. To store and manage this data efficiently, a database architecture has been designed. This architecture enables the merging of data from other observatories and sensors, which enables observation information to be retrieved quickly and efficiently. The database architecture is designed to store terabytes of data for each month of observation.

The database architecture depicted in Figure 31 is designed to efficiently manage and analyze satellite observation data. It integrates multiple sources, including tools for astrometry, object detection, and ephemerides. The architecture is divided into two primary components: the data sources and the database itself. The data sources consist of tools and datasets such as stellar indexes, SP3 satellite data, Earth Orientation Parameters (EOP), and software like SExtractor and YOLO, all of which contribute to generating or processing observational data. This information feeds into the database, which is organized hierarchically by satellite IDs, observation dates, and observatories. The database categorizes data into folders for each observation session, ensuring clarity and accessibility. Subfolders store specific outputs, such as raw frames, processed measurement files, and visualization graphs, alongside metadata like Two-Line Elements (TLE) or state vectors. The data acquired in sidereal tracking campaigns, i.e. for survey purposes, follow a similar structure, but without the ID level because is not known a priori the ID of the observed objects. Overall, this architecture combines modularity and adaptability, supporting collaborative efforts across multiple observatories. By integrating data sources like SP3 and EOP, it ensures accurate orbit determination and tracking, while its hierarchical design simplifies the retrieval and analysis of data for both catalogued and uncatalogued objects.

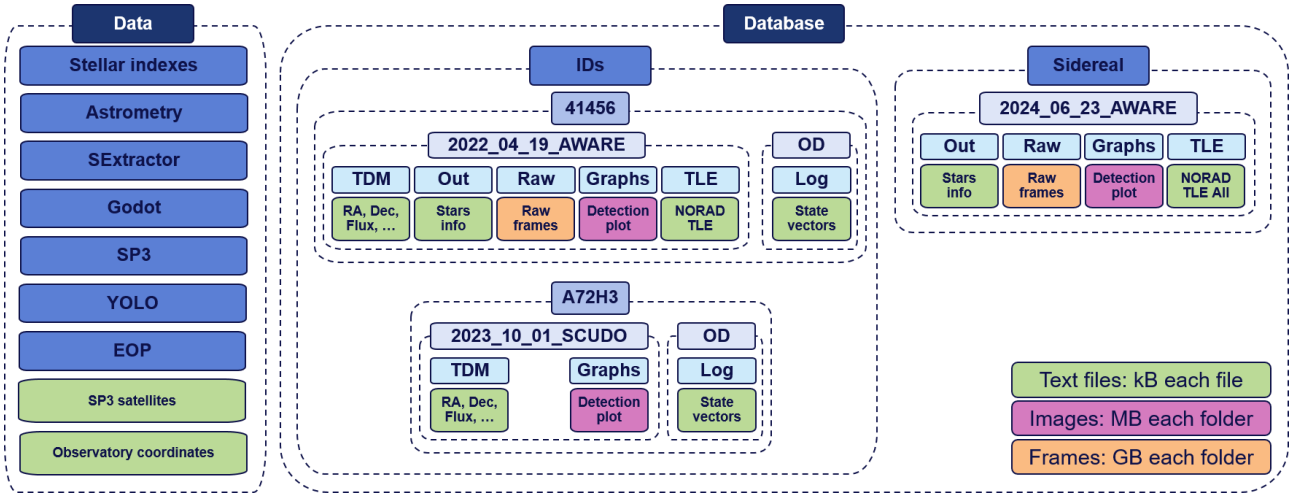


Figure 31. Database structure

A specific nomenclature was established for each file and folder within the database, allowing for quicker retrieval of key information contained in the image headers. This approach was designed to bypass the need to read each frame individually to obtain these details, reducing the time required for data analysis. In Figure 32 an example of a frame's filename adopted in the database.

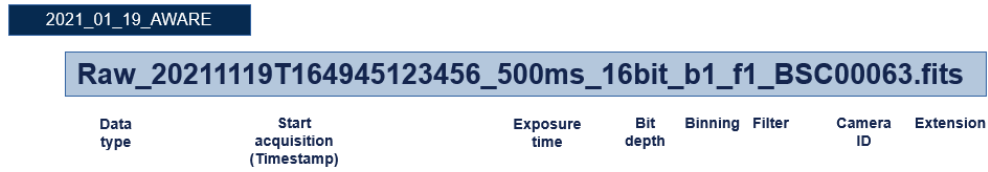


Figure 32. Frame nomenclature

Figure 33 presents an example of the data volume generated from 100 frames acquired by both AWARE cameras. As shown, the data size reaches approximately 4.5 GB for the acquisition and analysis of just 100 frames, illustrating the substantial data demands involved in high-frequency imaging. This example highlights the importance of efficient data management and processing strategies to handle the large volumes generated in operational scenarios.

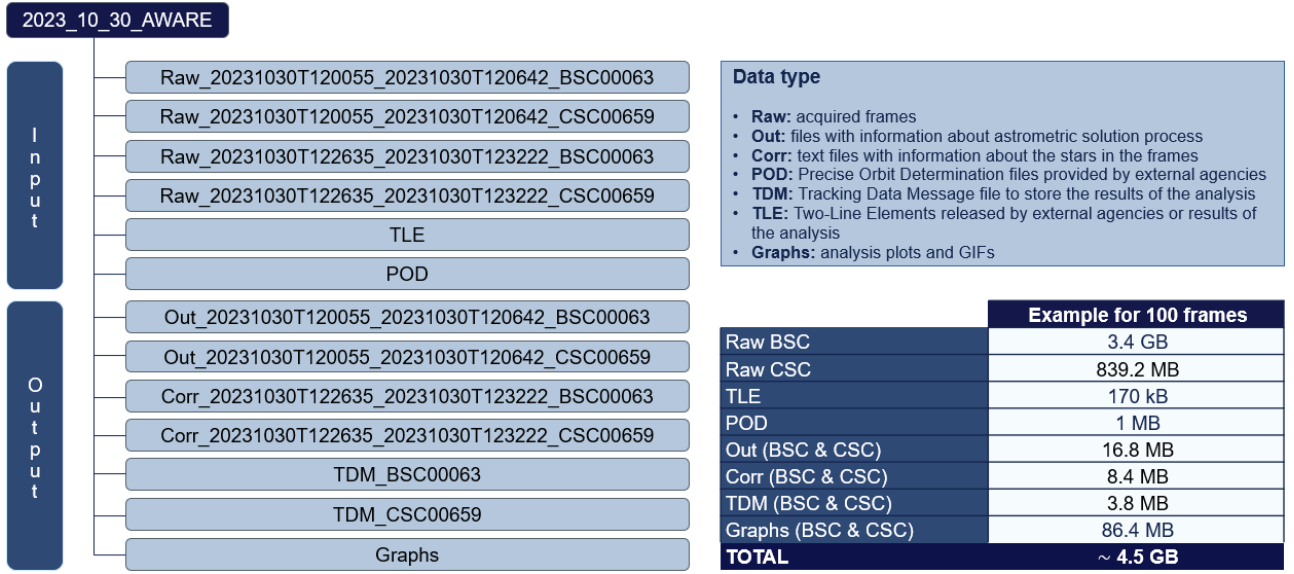


Figure 33. Example of data volume of 100 frames acquired by both camera of AWARE observatory

5. Frame analysis

5.1. Frame calibration

To correct phenomena due to the sensor such as the variation in quantum efficiency, vignetting, dark current, bias level and the gain for AD conversion it is necessary to calibrate the image. The standard photometric calibration is particularly important in cases where measurement accuracy heavily relies on the precision of the data collected from observations. In general, celestial objects are often observed under varying brightness and noise conditions, depending on the object's position in the sky, atmospheric conditions, instrumentation used, and other factors. This operation allows to obtain more precise and accurate measurements of the properties of celestial objects, such as brightness and dimensions. So, this preliminary calibration is needed to improve the object detection and its main feature estimation as well as reducing the artifact due to different kind of noise. The applied method is known as standard calibration [25] which can be expressed as:

$$IMG_{corr} = \frac{\overline{MFF}}{MFF} (IMG_{raw} - MDF) \quad (1)$$

where IMG_{raw} indicates the original raw image, IMG_{corr} is the corrected image, MDF the Master Dark Frame, MFF the Master Flat Field frame and $\overline{MFF}$ the average of the central pixels of the MFF . From this expression it can be seen that if the image were uniform the term $\frac{\overline{MFF}}{MFF}$ would be equal to 1.

For the standard calibration is required the acquisition of a certain amount of frame before the observation and after the acquisition of these frames, the calibration procedure follows the scheme reported in Figure 34:

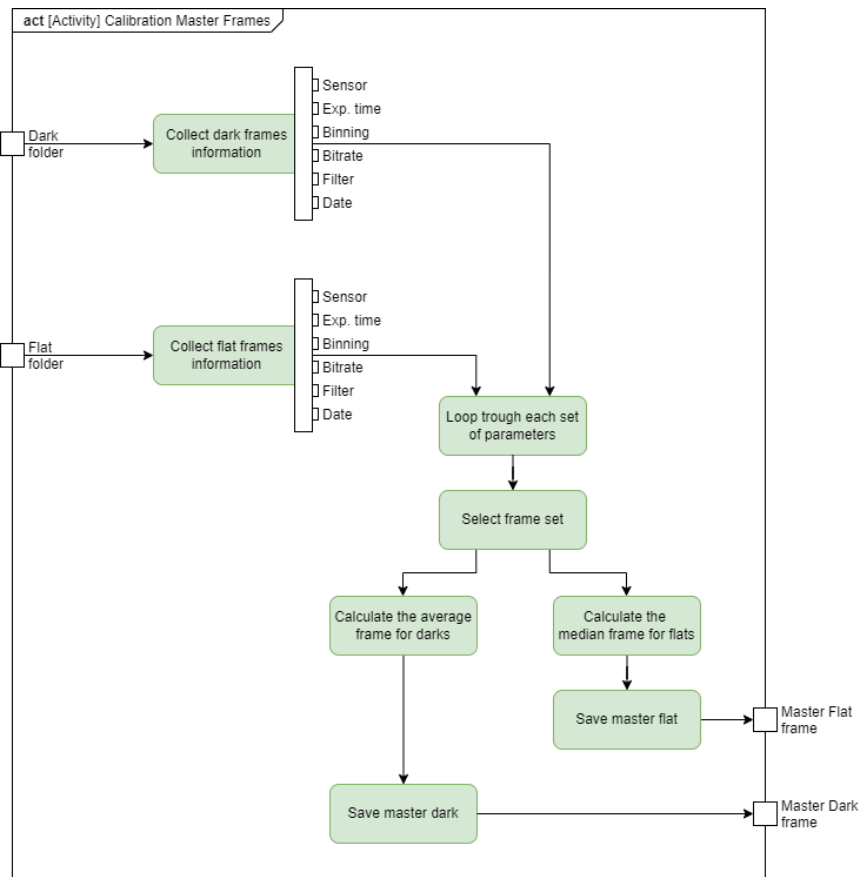


Figure 34. Calibration master frames activity diagram

The frames necessary for the standard calibration are obtained by the following procedure:

1. Calculate the average or the median of a few dark frames obtained with a time integration equal to that used for the astronomical subject, thus obtaining the Master Dark Frame (MDF).
2. Calculate the mean or the median of a certain number of flat-field frames, thus obtaining the Master Flat-Field Frame which, however, has yet to be corrected by its Dark.
3. Dark frames are taken relative to flat-field frames, i.e. with a time integration equal to that used for the astronomical subject. The result is the Master Dark Frame of the Flat (MDFF).
4. The MDFF obtained at point 3 is subtracted from the master flat-field obtained at point 2, thus obtaining the Master Flat-field Frame (MFF).
5. The master dark frame is subtracted from the raw image of the astronomical subject obtained in step 1.
6. The average value of the pixels of the central area of the flat-field master obtained in point 4 is calculated ($\overline{MFF}$).
7. The image obtained at point 5 is divided, pixel by pixel, by the average obtained at point 6 and the MFF. The calibrated image was therefore obtained.

The effect is very clear in Figure 35 that is one of the first that AWARE acquired when it was in Mammerdolf for the factory acceptance tests.



Figure 35. Standard calibration applied to an acquired frame of AWARE of XX nebula

The calibration frames are carefully selected and acquired based on key parameters such as the date of observation, exposure time, and sensor temperature. This approach ensures that the calibration frames closely match the conditions under which the observational data were captured, improving the accuracy of subsequent image correction and analysis. With these calibration criteria it is possible to mitigate potential biases or noise introduced by varying sensor temperatures and exposure times.

5.1.1. Dark frames

The dark frames are obtained by taking a photo at night and with the shutter closed. It is necessary to use the same conditions that were, or will be, at the time of the integration of the astronomical subject. In particular, it is necessary that the temperature of the sensor during the acquisition and that used to make the Darks is the same. The dark frame must be obtained with an integration time that is exactly the same as that used to obtain the image. The dark frame contains the thermal electrons accumulated during integration, but also the noise itself thermal and random variations in the number of accumulated thermal electrons, plus all elements contained in the bias frame. In Figure 36 is shown an example of the master dark frame.

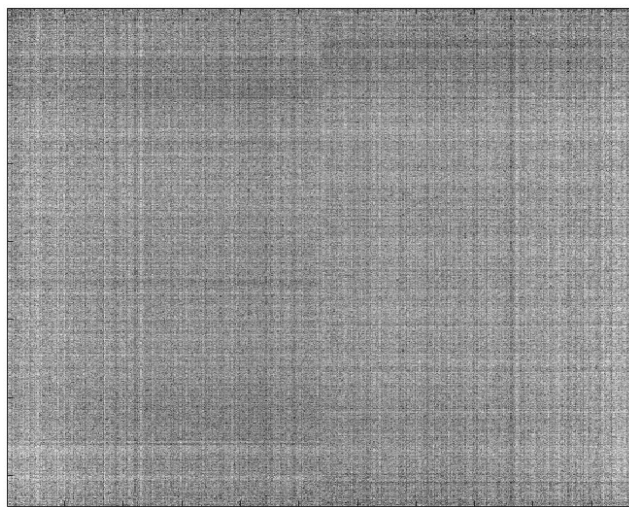


Figure 36. Example of Master Dark Frame taken by SCUDO observatory

To minimize thermal noise, the cameras used in the observatories are cooled to -10°C , reducing the impact of heat-generated noise on image quality. However, despite this cooling, CMOS sensors still experience other sources of noise that can degrade image clarity. These additional noise elements include amp glow, a sensor-specific issue that becomes particularly prominent in long-exposure images. Ampglow is a phenomenon in CMOS sensors where certain areas of the image appear brighter due to heat generated by the sensor's internal electronics during exposures. This effect occurs particularly around the edges of the frame where amplification circuits are located, resulting in unwanted brightening that can interfere with image quality. Proper calibration and image correction techniques are essential to mitigate this effect in astronomical imaging.

5.1.2. *Flat-Field frames*

The Flat-Field Frame is used to consider the variation in sensitivity (non-uniformity) of the pixels, the effects of any vignetting, specks of dust and dirt. These factors are not eliminated through the dark frame calibration, and for this reason the optical system used for shooting the flat-field frame must be the same used for taking the astronomical image. So, by evenly illuminating the entire sensor, the result is a map of the sensitivity of the sensor area, i.e. a map of the conversion efficiency of photons into electrons by each pixel. The flat-field frame can be obtained by taking a photo of a light source, so that the sensor is uniformly illuminated. This calibration frame can be acquired by taking a photo during sunset by placing a well-spread white sheet in front of the lens or by using a special tool for generating flat-field frames. The exposure time to be used is that necessary to obtain about 50% of the value for sensor saturation. In the AWARE station these calibration frames are acquired during the sunset pointing the telescope in the opposite direction of the Sun in a sky area that not present clouds and present the most uniform illumination as possible. Figure 37 shows an example of master flat frame.



Figure 37. Example of Master Flat Field Frame taken by SCUDO observatory

Mini-SURGE does not have an automatic system for acquiring flats from remote, therefore the calibration is performed only using dark frames to produce the master frame and subtract it from the original image.

5.2. Automatic focus

The Laplacian filter is a second-order derivative filter used in image processing to highlight areas of rapid intensity change and is therefore often used for edge detection. It works by computing the second derivative of the image, which effectively measures the rate at which the gradient changes. This makes it particularly sensitive to regions of an image where intensity varies sharply, such as edges. The Laplacian operator is defined as:

$$L(I) = \Delta^2(I) \quad (2)$$

Where Δ^2 is the Laplacian operator and I the image. A blurry image lacks well-defined edges. When the Laplacian of such an image is computed, the response tends to be uniform across the entire image. Consequently, the variance of the Laplacian for a blurred image is lower compared to that of a sharp image. Therefore, to determine if an image is in focus, the strategy is to maximize the variance of the Laplacian. In particular:

$$\sigma_{L(I)}^2 = \frac{1}{N} \sum_{i=1}^N (L(I)_i - \mu_{L(I)})^2 \rightarrow \text{optimal}_{focus} = \max(\sigma_{L(I)}^2) \quad (3)$$

Where $L(I)_i$ is the value of the Laplacian in the pixel i , $\mu_{L(I)}$ is the mean value of the Laplacian and N is the number of the image pixels. The focuser is initially moved to an extra focal position. Subsequently, ten images are captured, each with an exposure time of one second. The Laplacian operator is then applied to all the captured images, and the variance is calculated as shown in Figure 38.

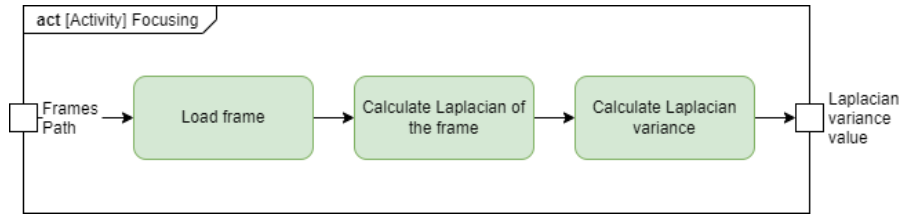


Figure 38. Focusing

This process is repeated ten times, with the focuser being moved to different positions each time. The collected data points are then fitted with a Gaussian curve. The maximum of the fitted curve is found, and the corresponding x-position is recorded. Finally, ten more images are taken to calculate the maximum value and compare it with the expected value. The temperature, the encoder position, and the fitting error relative to the measurements are recorded. In Figure 39 is shown an example of three images with different focus position.



Figure 39. Three frames evaluated during the focusing routine: the left frame is in the intra-focal position, the right frame is in the extra-focal position, and the center frame shows the optimal Laplacian variance achieved at the end of focusing.

5.3. *Stellar field resolution*

The astrometric solution of astronomical images refers to the process of identifying and positioning celestial objects in the frames into a reference celestial map. This process is important for studying and analysing the properties of celestial objects and their spatial relationships. This operation is performed using astronomical reference catalogues, which contain the celestial coordinates of a large number of known celestial objects. These catalogues have been created through past observations of celestial objects and contain information about the positions, luminosities, and other properties of celestial objects. The astrometric solution is typically performed using specialized software that can compare astronomical images with reference catalogues and identify the celestial objects present in the image. These software may use shape recognition algorithms, which can automatically identify the celestial objects present in the image.

The stellar field resolution is needed to associate to each pixel the correspondent celestial coordinates. To do this is necessary to determine which stars are present in the FoV, or in the frame, and therefore it is necessary to solve the stellar field of the images (Astrometric solution). Astrometric solution is carried out thanks to the use of the Astrometry.net software which outputs the solved image, or the image in which are present the celestial coordinates for each pixel coordinate, and a text file (corr file). The main reasons under the choice of the Astrometry.net suite are:

- Reliable and robust system that takes as input an astronomical image, and returns as output the pointing, scale, and orientation of that image (the astrometric calibration or WCS information).
- The system requires no first guess and works with the information in the image pixels alone.
- The success rate is very high: 99.9 percent for shallow UV and optical imaging survey data, with essentially no false positives.

- Generate consistent and standards-compliant meta-data for all digital and digitized astronomical imaging.
- Optimized for server usage: Astrometry.net is already optimized for server usage but requires attention as it could crash the server due to the parallelization of the processes.

In FATE the stellar field resolution is the API that execute an Astrometry.net command to find the astrometric solution of a frame and to create the files necessary to convert between pixel and celestial coordinates. The diagram of the operations performed by FATE is shown in Figure 40.

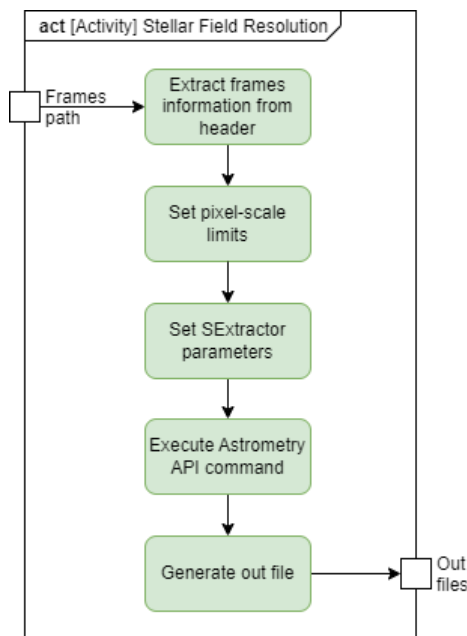


Figure 40. Stellar field resolution activity diagram

To save the information of the stars that Astrometry.net have used to solve the star field, the corr file is created, and it contain for each star in the FoV the most relevant information such as celestial coordinates, pixel coordinates, and bolometric (B) and visual (V) catalogue magnitudes. The information about the stars are related to the stellar catalogue used in this procedure.

To find the astrometric solution of a stellar field, the first step is to recognize the stars in the image. Astrometry.net can find autonomously the stars, but to have a better result, in term

of centroid precision, the use of an external software is required. This software is called SExtractor and improves the centroid calculation especially when the stars are stripes. The stellar field resolution requires time that depends on several factors, for example the quality of the image, the number of the stars in the FoV, etc. This process can be very slow, especially if all the star indexes in a catalogue are used for each frame. Also, the choice of the catalogue is fundamental to obtain the correct information regarding the stars in the various frames. The star catalogue used to solve the star field by Astrometry.net is the Tycho-2 [26]. The Tycho-2 Catalogue contains positions, proper motions and two-color photometric data for the 2.5 million brightest stars in the sky. The magnitude errors are lower than 0.1 for stars with magnitude 10 and then gradually rises to at most 0.4 at magnitude 12 and fainter. The position and magnitude measurements of Tycho-2 stars are based on observations made by the astronomical satellite Hipparcos, built by the European Space Agency in order to map the entire sky. The United States Naval Observatory (USNO) used Hipparcos data for the compilation of the Astrographic Catalog / Tycho Reference Catalog, including about one million stars, therefore the use of Tycho-2 was preferred both for the high number of stars than to be precise in terms of magnitude.

There are instances when star field images cannot be successfully resolved due to various limiting factors. In some cases, the number of visible stars may be insufficient for accurate field recognition, or the stars may appear excessively streaked due to motion during exposure. Additionally, atmospheric conditions such as strong winds or cloud cover can further degrade image quality, making it challenging to obtain a clear, stable view of the star field. These factors can significantly impact the reliability of star recognition and require careful monitoring and calibration to mitigate their effects on observational accuracy. The time required to find the astrometric solution for a single frame could be up to 10 minutes if it is not limited in the software input. If the aim is the analysis of an already recorded sequence of frames, it is convenient to first find the astrometric solution of all the frames and then start the analysis. This strategy allows to drastically reduce the video analysis time as

Astrometry.net, parallelizing the star field resolution process, resolves multiple images at the same time. If the resolution of the images were sequential, it is necessary to wait for the previous image to be resolved to resolve the next one and it would waste time. It is important to notice that in a live object tracking this operation must be sequential because the coordinates to point the telescope depend on the object coordinates retrieved in the previous frame. To improve the software's processing speed, without losing the astrometric solution quality, various test has been performed. Specifically, the tests aimed to optimize the following aspects:

- Astro-referentation processes parallelization: allows to analyse several frames simultaneously based on the number of processors of the server to be used.
- Tycho2, 2MASS e Gaia DR2 star catalogues selection: frames from videos of several objects, both LEO and GEO, have been astro-referentiated. This analysis evaluates the quantity of astro-referenced frames and the information contained in the corr file (quantity of stars, catalogue magnitude and position).
- Stellar indices selection: once the star catalogue for the astro- referentation of the frames has been selected, the star indices must be chosen to best approximate the frames FoV dimensions.
- Polynomial order
- Exposure time

One of the main parameters to consider for the stellar field resolution is the exposure time, since a too high value causes that the stars in the field of view to appear as excessively long strips, resulting in a in failure of the star field astro-referentation. Conversely, if a short exposure time is used, not enough stars might be identified for the astrometric resolution, because the stars would not be visible. Regarding the object, a high exposure time value could lead to a saturation of the pixels that represent the object in the field of view. Instead, a low exposure time value causes a lower signal to noise ratio of the object that make it not visible. Other parameter that needs to be checked are the binning, the frame rate, the pixel depth (8, 12 or 16 bit) and whether to use global or rolling shutter. For the cameras of the

AWARE observatory, global shutter is used on the Balor and rolling shutter on the Marana. Both use binning 1 and pixel depth 16 bits. It was possible to choose these parameters because the good light conditions and the excellent instrumentation make it possible to see even very faint objects without having to sacrifice image quality (i.e. by using binning or reducing the pixel depth). In Table 5 are shown the percentage of astro-referentation divided for exposure time, orbit type and stellar catalogue for each camera of the AWARE observatory.

Table 5 Astro-referentation tests with Balor and Marana cameras using Tycho2 and DR2+Tycho2 stellar catalogues

BALOR					
Orbit type	N frames	Exp time	NORAD ID	AR percentage DR2	AR percentage TY2
LEO	30	1ms	53963	0%	0%
LEO	30	60ms	07209	30%	90%
LEO	30	100ms	44212	0%	20%
LEO	10	250ms	53027	0%	0%
MEO	30	100ms	43622	87%	90%
GEO-SYNC	30	4s	37256	100%	100%
GEO-SYNC	30	5s	36828	100%	100%
GEO-SYNC	6	10s	13907	0%	50%
GEO	30	4s	29495	100%	100%
GEO	30	5s	40146	100%	100%
MARANA					
Orbit type	N frames	Exp time	NORAD ID	AR percentage DR2	AR percentage TY2
LEO	30	1ms	53963	0%	33%
LEO	30	100ms	07209	90%	83%
LEO	30	120ms	51100	0%	100%
LEO	30	200ms	51889	0%	30%
LEO	30	500ms	44212	0%	90%
MEO	30	10s	43622	0%	83%
GEO-SYNC	30	4s	27831	47%	100%
GEO-SYNC	30	5s	37384	83%	100%
GEO-SYNC	2	10s	37763	50%	100%
GEO-SYNC	6	20s	13907	0%	100%
GEO	30	4s	29495	60%	100%

In the tests it appears that the Tycho2 stellar catalogue is better than the DR2+Tycho2 for both large and small FoV. In the AWARE observatory, exposure time is calculated in advance based on the satellite's predicted pass, ensuring that the resulting star trails are as constant in length as possible. This approach helps maintain uniformity in star streaks throughout the satellite's passage, which is crucial for achieving consistent astrometric accuracy during the observation.

Strictly correlated to the astrometric solution is the world coordinate system (WCS). The stellar field resolution associate to each pixel the correspondent celestial coordinates, so the image is projected in the celestial sphere. Is defined WCS procedure, the generalized method for assigning physical (or celestial) coordinates to FITS images. Once the stellar field occurs, the header of the image is modified due to the WCS procedure. To do this operation a change of the coordinate is required, and all the details of these operation are written in [27]. The conversion from pixel coordinates to celestial coordinates depends on how the astrometric solution is found, specifically, one of the main aspects is the degree of the interpolating polynomial that is used to map the image. Various tests were carried out to evaluate the degree of the polynomial to be used for the various systems and it was found that it is appropriate to use a polynomial of degree 3 for the Balor as well as for the Marana. The degree of the polynomial depends on the size of the field of view and the number of stars present in the image. The greater the field of view, the greater the degree of the interpolator polynomial must be. Moreover, the greater the number of stars present in the FoV, the greater the degree of the interpolator polynomial that must be used. The images in Figure 41 shows the difference in RA and Dec between the star positions calculated by FATE and those reported in the star catalogue.

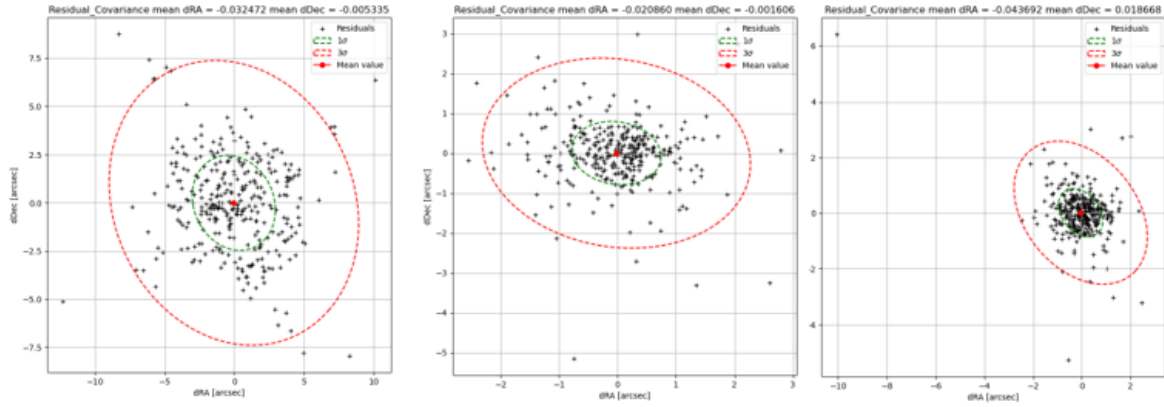


Figure 41 Accuracy in the astro-referentation using polynomials with order 1 (left), 3(centre) and 5 (right)

As can be seen from Figure 41, the order of the polynomial that is chosen is the one that minimizes the standard deviation of the measurements and positions the ellipse of covariances as close to the centre as possible. The same analyses were performed for the observers of Sapienza and very similar results were obtained. In Figure 42 are shown two frames with correspondent covariance ellipsoid that highlight the robust astrometric solution obtained thanks to the use of an optimised local version of the astrometry.net software. These two graphs shown the difference between the position of the stars present in the star catalogue, and the position of the same stars retrieved by astrometry.net and, as you can see in this example, we have an accuracy, or standard deviation, less than one arcsecond at one sigma, that means that we can retrieve with high precision the celestial coordinate of an object in the frame.

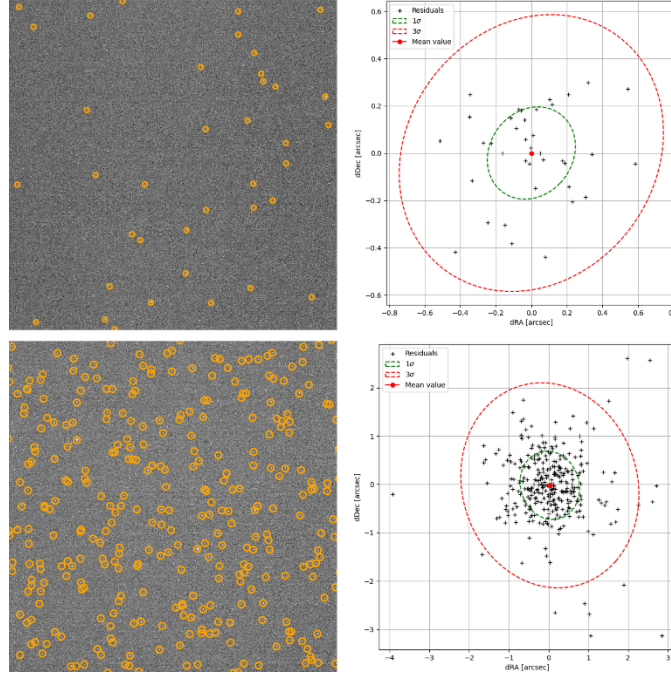


Figure 42. Comparison between stars celestial coordinates of Astrometry.net and the stellar catalogue

Additionally, collecting photometric data relies on Plate Solving since this procedure also provides information on the flux and magnitude of the stars present in the sensor FoV. This information is directly retrieved from the catalogue used for the astrometric solution; thus, selecting an appropriate catalogue is crucial. The ATLAS All-Sky Stellar Reference Catalog (“ATLAS-REFCAT2”) [28] was chosen to analyze SCUDO frames when using photometric filters, as it provides standard magnitude data for stars within the Sloan filters wavelength range. Instead, stars from the Gaia EDR3 catalogue were employed for the astrometric-referencing process of Mini-SURGE images.

5.4. TLE propagation

The procedure begins with loading the station's position, the Two-Line Element (TLE) of the object, and the planetary ephemerides. Using the SGP4 model, the TLE and the station's position are propagated to determine the satellite's trajectory. Simultaneously, the position of the Sun is extracted from the planetary ephemerides. With this information, the elevation and azimuth of the satellite are calculated. Subsequently, the celestial coordinates of the

satellite, specifically the right ascension and declination, are computed. The phase angle, which indicates the satellite's position relative to the Sun and the observer, is also determined. Finally, all these details are combined into a single TDM, providing a comprehensive file for further analysis. The procedure is illustrated in Figure 43.

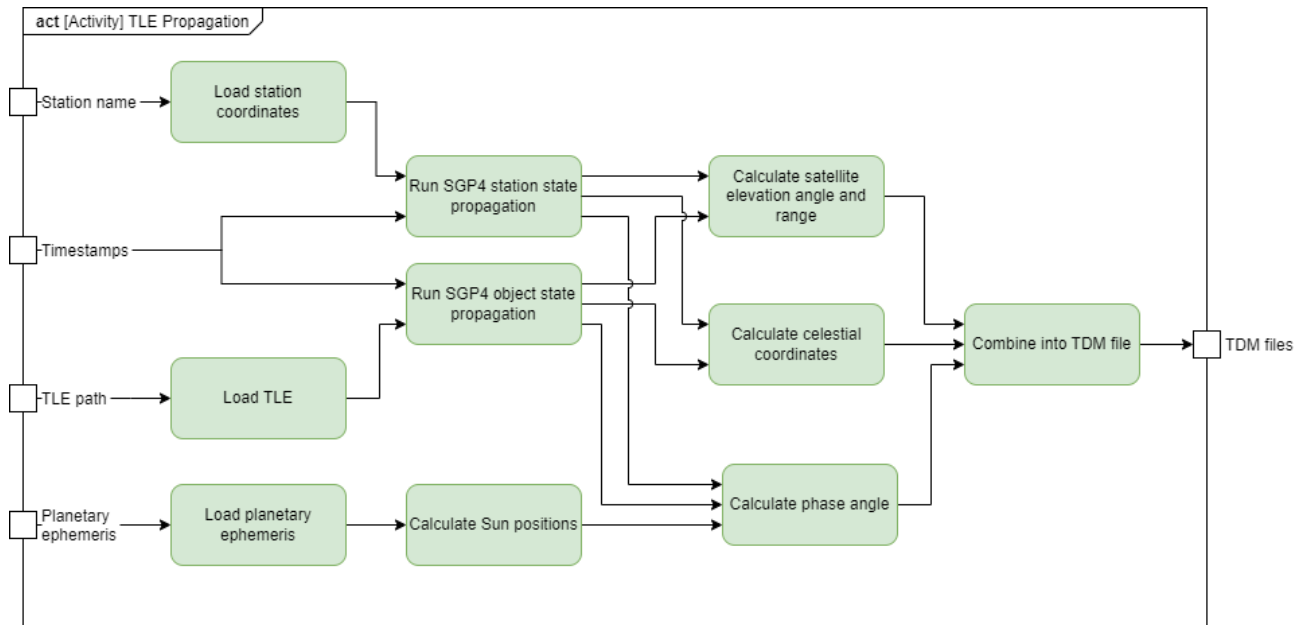


Figure 43. TLE propagation activity diagram

The phase angle (Figure 44) is fundamental for calculating the quantity of light reflected by the object and it is one of the main parameters to take under control to understand the object visibility.

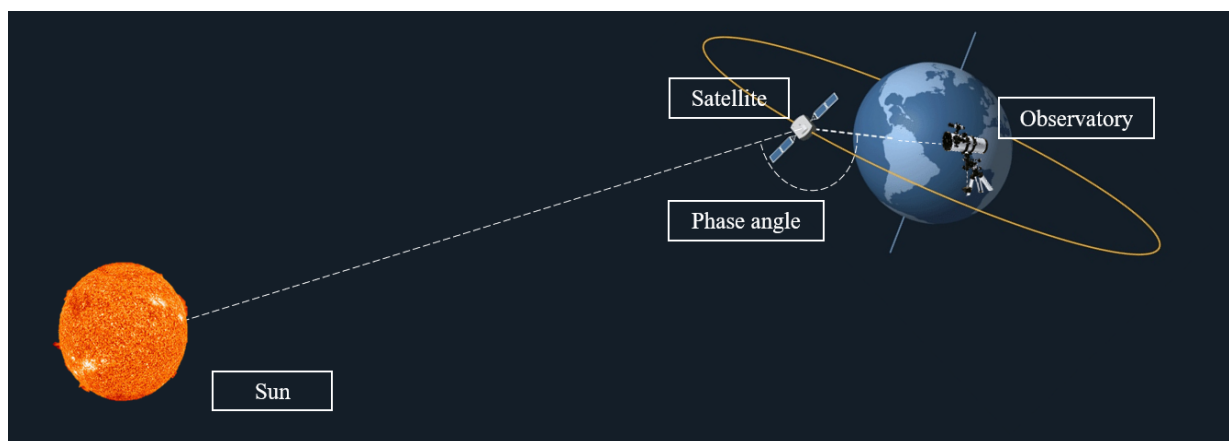


Figure 44. The phase angle, observer-object-sun, needed to compute the amount of light reflected by the object

The phase angle allows to calculate the diameter of Lambert's sphere, which is considered a reference parameter for the object's dimension. A bond albedo of 0.2 is assumed for all

objects, and the phase function is assumed to be Lambertian, though it is well understood that for rocket bodies, spacecraft, and complex shapes the phase function is a complex combination of specular and Lambertian phase functions. The system of equations to calculate Lambert's parameter is shown below [29]:

$$\begin{cases} \mathcal{F}(\phi) = \frac{1}{\pi} (\sin(\phi) + (\pi - \phi)\cos(\phi)) \\ m_{obj} = m_{sun} - 2.5 \log_{10} \left(\alpha \frac{d^2}{4R^2} \rho_{bond} \mathcal{F}(\phi) \right) \end{cases} \quad (4)$$

where $\mathcal{F}(\phi)$ is the phase function, ϕ is the phase angle, m_{obj} is the object's magnitude, m_{sun} is the sun's magnitude, α is equal to $\frac{2}{3}$ for a Lambertian sphere, d is the Lambertian diameter, R is the object's range, ρ_{bond} is the bond albedo, characteristic of object's reflection, equal to 0.2 for aluminium. In Figure 45 is shown a graph in which all the previous quantities are plotted to visualize the main geometrical parameters during the acquisition.

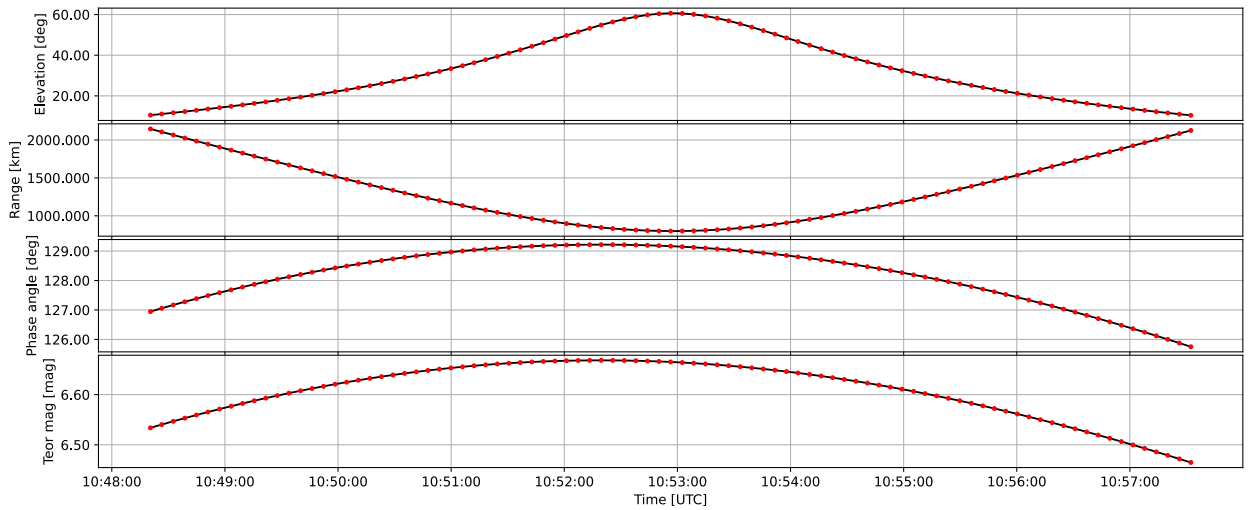


Figure 45. TLE propagation

5.5. Objects centroid

The centroid calculation routine depends on the observation method that is used for observing the object. Different observation method implies different image and so the stars and the object appear in different way. To extract the centroid of an object in the frame four steps are needed using computer vision-based method:

- ROI selection (A)
- Contrast enhancement (B)
- Binarization (C)
- Shape extraction and centroid calculation (D)

An example of these steps is shown in Figure 46.

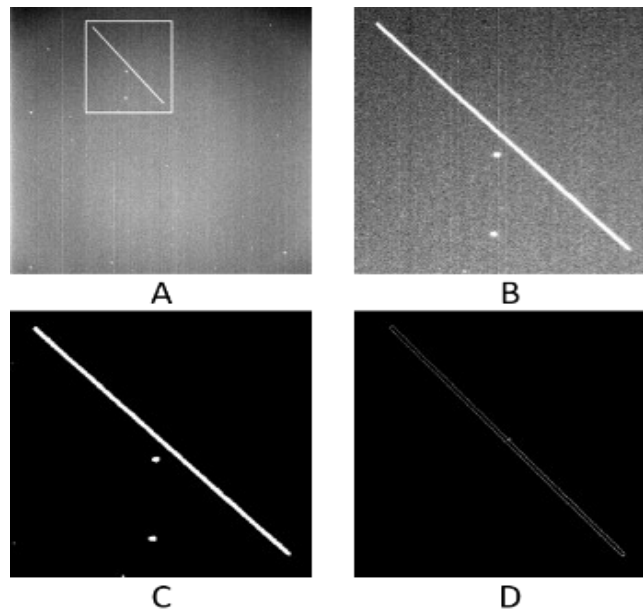


Figure 46. Typical steps for object detection in astronomical images

In astrometry, one of the most used and classical algorithms is SE. The main steps of SE algorithm are shown briefly in the following list:

1. Measure the background and its RMS noise (background and RMS maps).

SE estimates the background of the image as well as the RMS noise in that background, mapping both. The image is divided in areas with size equal to BACK_SIZE. In these areas,

the mean and the σ of the distribution of pixel values are computed. Then, the most deviant values are discarded and median and standard deviation σ are computed again. This is repeated until all the remaining pixel values are within mean $\pm 3\sigma$. If σ dropped with less than 20% per iteration, the field is considered not crowded. The value for the background in the area is:

- the mean in the non-crowded case,
- $2.5 \times \text{median} - 1.5 \times \text{mean}$ in the crowded case.

Both the mean and the median are the ones computed in the last iteration. The mean is simply the average, while the median is the average of all the values except the most extreme one. The background map is a bi-cubic-spline interpolation over all the areas of size BACK SIZE, after filtering. So, the choice of BACK SIZE is very important: a too small area will result in the background estimate to be partly object flux, while with a too large area will cause small scale variations to be not taken into account.

2. Subtract background

The background estimation can require lot of time, so in FATE the background is calculated only in the ROI of the object. Then, the background is subtracted to the ROI.

3. Filter (convolve with specified profile).

The convolution of the image with a specific profile essentially smooths the image, and so is a sort of filtering. There are some advantages to applying a filter before detection, in fact it may help detect to faint or spread objects.

4. Find objects (thresholding).

The threshold parameters indicate the level from which SE should start treating pixels as if they were part of objects, determining parameters from them. There are three requirements for a candidate objects:

- All the pixels are above the detected threshold.

- All these pixels are adjacent to each other (either corners or sides in common).
- There is more than the minimum required number of pixels

5. Deblend detections (break up detection into different objects).

Deblending is the part of SE where a decision is made whether a group of adjacent pixels above detected threshold is a single object or not. As an example, suppose there is a little island of adjacent pixels above the threshold. It could be an object, or maybe several of them really close to each other. To cut this up into different objects, SE first defines a number of levels between the threshold and the maximum count in the object. This is set by the deblend threshold parameter. The levels are spaced exponentially. SE then constructs a “tree” of the objects (Figure 47), branching every time there are pixels above a threshold separated by pixels below it [16].

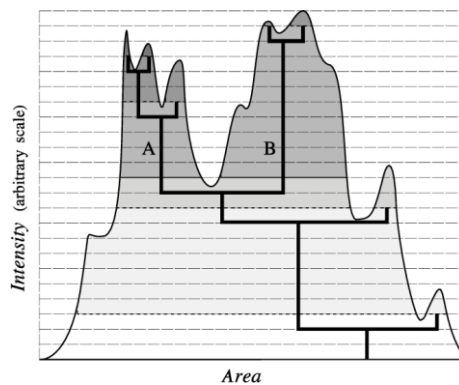


Figure 47. SExtractor deblend tree

6. Measure shapes and positions and perform photometry.

The photometry and so the centroid extraction depends on the shape of the object that is related to the observation method used for the observation.

In Figure 48 is shown the analysis of a ROI using a modified version of SE in which is added the convolution step needed to highlight the gaussian structures present in the ROI in the TLE tracking mode.

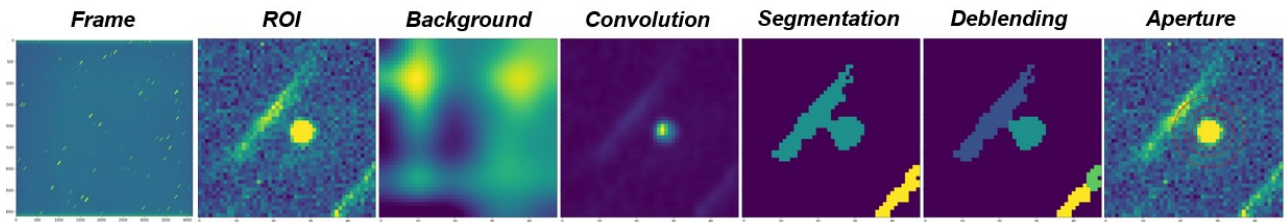


Figure 48. SExtractor procedure to perform aperture photometry

Exists different observation methods, the four most used are the sidereal, TLE, fixed and live tracking.

5.5.1. Sidereal tracking

In this observing mode the object appears as a streak, while the stars as dots because it involves maintaining a fixed pointing within the inertial reference frame. This technique can be used for observations from LEO and GEO, allowing for fast stellar field resolution due to the dot shape of the stars. This strategy typically captures 1 to 10 frames per minute with exposure times less than 10 seconds. Usually the object to be photographed is the largest object in the image, for which identification could be simple, but there are several other cases to consider. For example, the object may have an uncontrolled attitude motion, causing the tracklet to be discontinuous or with non-constant brightness along-track. Another case is that the object to be photographed is not the only one present in the field of view.

A strategy is then required to identify the correct object in the image and that correctly identifies the beginning and end of the track. This discrimination can be done quite easily if the object is catalogued and therefore its TLE is available. This TLE is used to obtain the pixel coordinates at the beginning of the exposure time and has the end of the exposure time, thus being able to simulate the size of the trace to be identified. In this way, it is possible to have a good estimate of the position of the object in the frame and of the size of the tracklet that needs to be identified. In Figure 49 is shown an example of a frame with two objects inside.

To identify the correct one the TLE is propagated and a simulated tracklet is projected into the frame. The tracklet that is closest to the simulated one is the correct object.

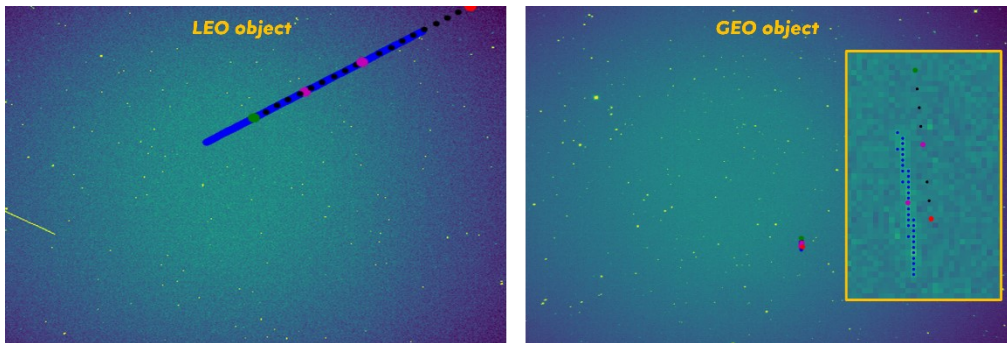


Figure 49 Example of frame with two objects. On the left the original frame and on the right the frame with the projected tracklet in blue.

Once the correct object is identified, is possible to proceed with the aperture photometry. In Figure 50 is indicated in black the predicted tracklet, the green dot is where the tracklet starts, i.e. the beginning of the exposure, and the red one is where the exposure ends.

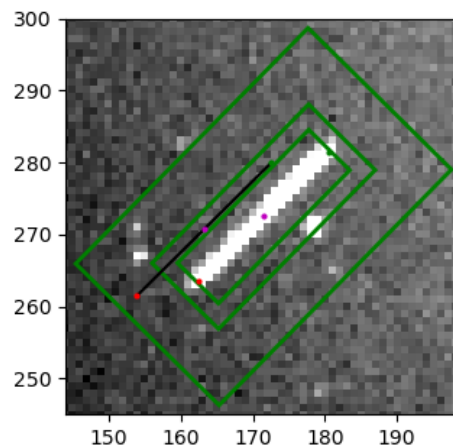


Figure 50. Tracklet identification

For the aperture photometry, in the sidereal tracking case, the rectangles are used instead of the circles due to the shape of the object. The rectangle fits better the tracklet of the object. The outer rectangular annulus is used to estimate the background, while the inner one for the flux. At this point it is possible to calculate the centroid of the object that is the centre of mass of the tracklet.

5.5.2. *TLE tracking*

For the object tracking method the steps for the object recognition are the same as is sidereal tracking, but in this case the object is a dot. This method is particularly useful for observations of LEO objects, in which it is possible to capture up to 20 frames per second, with an exposure time of less than 0.1 seconds. The main parameter to take under control is the exposure time, since a too high value of this means that the stars in the field of view are represented by too long strips with consequent failure in the resolution of the star field. Conversely, if a too short exposure time is used, not enough stars are identified for the astrometric resolution, because the stars are not visible. Regarding the object, a high exposure time value could lead to a saturation of the pixels that represent the object in the field of view. Instead, a low exposure time value involves a lower signal to noise ratio of the object that make it not visible. Mainly is necessary to check the binning, the exposure time, the frame rate, the image type (8, 12 or 16 bit) and whether to use global or rolling shutter.

In object tracking mode, the object is represented by a point while the stars by streaks. Recognizing the object in the field of view therefore means recognizing a point within the image. This spot can be of different sizes depending on the type of object, its brightness, and its size. During object tracking, the point representing the object is not always in the same position and will not always be in the centre of the image.

Two different strategies have been evaluated to correctly identify the object in the frame. The first one is based on an algorithm that identify the object in the first frame, calculates the coordinates of the centroid, and uses these coordinates as a first guess to derive the coordinates in the second frame. This operation continues until the last frame that makes up the video. The second one uses the TLE as a first guess for the object position and around these coordinates create a ROI in which the object is searched.

The first strategy is not based on the TLE, but rather on finding the point that represents the object in the first frame. This task is often difficult as, in this observational mode, short exposure times are used, and the object is not easily identifiable. If the object does not change

its position too much during the first frames that make up the video, the strategy is to add a certain number of initial frames, so that the values of the pixels that make up the object add up and the object is the brightest object in the sum image as shown in Figure 51.

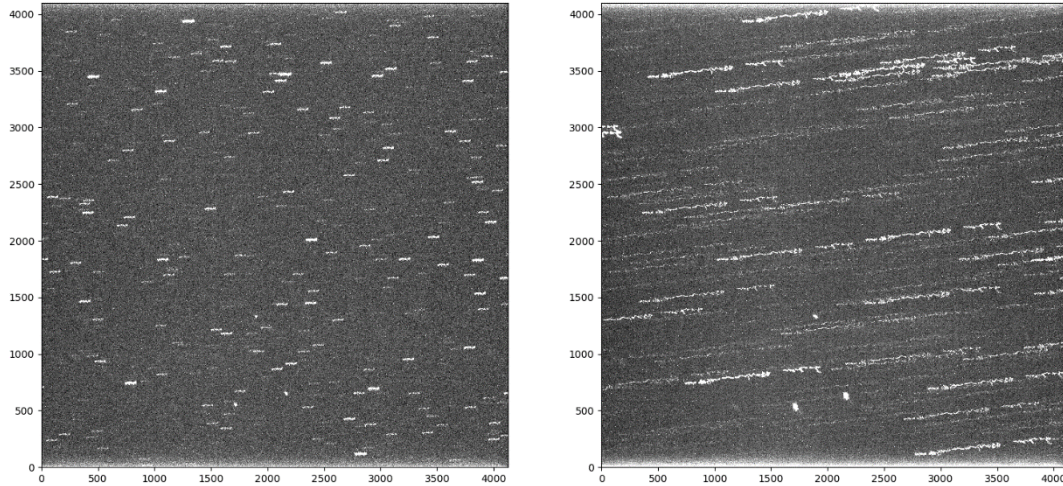


Figure 51 Comparison between single Balor frame with 4s of exposure time (left) and 10 consecutive frames summed (right)

Once the brightest object in the field has been identified, the pixel coordinates of this object are found and used as a first guess for the position of the object in the first frame. Around those pixel coordinates a ROI of a certain size is established. The size of this ROI cannot be too small, because there is a risk that it does not contain the object, but also shouldn't be too large, as it could contain too many objects and reduce the quality of the calculation of the centroid. If different objects (stars or other satellites) are present in the ROI, the object that is closest to the previous coordinates, and is the most circular, is chosen as the correct one. To calculate the coordinate of the centre of the object (called centroid) an algorithm based on the identification of the contours is used. Once the centroid in the first frame has been found, it is used as a first guess for the object coordinate in the second frame. Around this coordinate, a ROI of appropriate size is created, in which the object must be present. At this point the centroid is calculated as previously described, correcting the first guess. This approach requires that the object must be present in the first analysed frame.

There are some objects that do not have a constant brightness, either because of their attitude motion, on the weather conditions (i.e. clouds, winds, etc.), or because they are objects that

have an on-board LED and therefore in some frames the object may not be visible. In these cases, the previous algorithm must be updated because, in the frames where the object is not present, it is not possible to calculate the centroid of the object. It is therefore necessary to predict the coordinates that the object will assume in those frames using for example a Kalman filter or the coordinates in the previous frame can be used. The second strategy use SExtractor (SE) to determine the centroid of the object. The TLE of the object is propagated with SGP4 at the time of the frame, and the celestial coordinate of the object are converted into pixel coordinates. A ROI around the propagation is created and the object is searched inside this ROI. The two strategies have different advantages and disadvantages which are summarized in Table 6:

Table 6. Pro/cons in object tracking using the TLE

Without TLE - Pros	Without TLE Cons
Fast because the ROI is smaller.	Difficult to always find the first frame where the object is present
Fewer errors in the object identification because centred on the previous coordinates	Coordinates of the first frame are difficult to obtain with high certainty
Possible improvement with Kalman filter for predicted position and ROI size with covariance	
Possible use for object tracking without TLE	
With TLE - Pros	With TLE - Cons
Possible parallelization because it does not need the coordinates of the object in the previous frame so each frame can be analysed separately from the others	Slow because the ROI is always the same size
It is possible to automatically distinguish the correct object if there are multiple satellites	Object may not be in the ROI because it is too small, or the object is too far from the TLE
	It cannot be used for uncatalogued objects

5.5.3. Fixed tracking

Fixed tracking refers to maintaining a constant pointing direction in the topocentric reference frame, making it particularly well-suited for observing GEO objects. This technique typically enables the capture of 1 to 2 frames per minute, with exposure times exceeding 5

seconds. In these images, GEO objects appear as stationary points, while stars and objects in other orbital regimes produce streaks due to their apparent motion relative to the observer. Fixed tracking is employed by the Mini-SURGE system, which lacks a motorized mount capable of compensating for Earth's rotation. A common approach in this mode is the use of image stacking to enhance the detection of GEO objects. Because GEO objects remain stationary on the same pixels across consecutive frames, their signal accumulates linearly when the images are stacked. In contrast, the background, composed of streaking stars and noise, does not sum coherently, allowing it to be effectively suppressed. This technique enhances the signal-to-noise ratio, improving the detection of faint GEO objects while minimizing interference from the moving background.

5.5.4. Live tracking

This tracking method enables satellite observation even in cases where no prior data, such as ephemerides or TLE sets, are available. The process begins with the Stare phase, where an initial measurement of the satellite's position is acquired, allowing the system to establish a baseline for tracking. This initial phase leads into the Chase phase, a dynamic sequence where measurements extracted from incoming images are continuously fed into an orbit determination algorithm, updating the satellite's estimated position and refining the tracking commands through a closed-loop system.

The tracking approach combines elements of both sidereal and TLE-based tracking. Initially, sidereal tracking is used, causing the satellite to appear as a streak across the frame while stars remain stationary. As the Chase algorithm iteratively updates, the tracking adjusts in real-time to the satellite's motion, gradually shortening the satellite's streak in successive images. Eventually, as the system achieves synchronization, the satellite appears as a stable point (a circular shape), indicating successful tracking alignment. During this process, each captured image is analyzed in a continuous loop: the satellite is identified, measurements are taken, and these are fed into an Extended Kalman Filter (EKF). The EKF then updates

and propagates the satellite's state, providing real-time adjustments to the telescope and camera commands for precise, automated tracking.

5.6. Centroid algorithm validation

To verify the correctness of the algorithm for calculating the centroid, it is possible to proceed by making a comparison between the centroids obtained with FATE and those from Astrometry.net. The processing chain of Astrometry.net is similar to that of FATE, so it is possible to verify the correctness of the FATE algorithm by comparing the coordinates of the stars that FATE finds in the image, with the coordinates that Astrometry finds. Once we have verified that the x, y coordinates of the stars obtained from FATE were similar to those of Astrometry.net, we then proceed with the comparison between the celestial coordinates (RA, Dec) of the stars found with FATE, with the coordinates of the same stars but from the star catalogue. For this comparison we need to use the conversion from pixel coordinates to celestial coordinates, therefore the accuracy of this result depends both on the correctness of the calculation of the centroid, and on the correctness in the astro-referencing process.

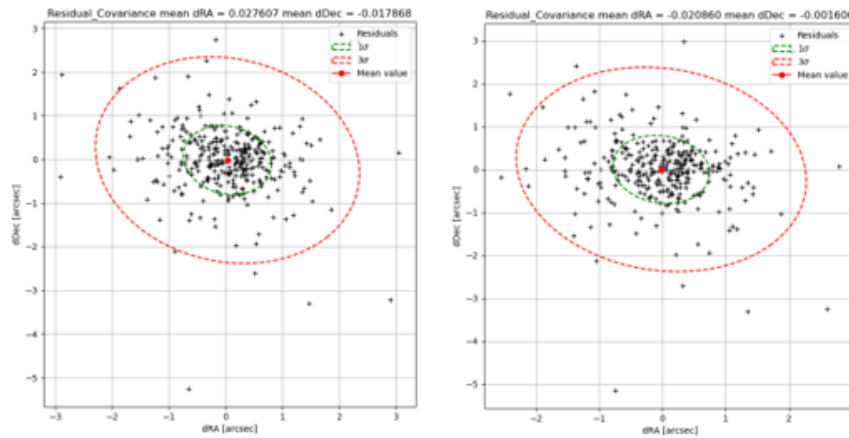


Figure 52 Accuracy in the stars position w.r.t. the stellar catalogue with Astrometry.net (left) and with FATE (right)

As can be seen from Figure 52, the errors obtained are smaller in FATE's results, which confirms that both the algorithm for calculating the centroid and the conversion from pixel coordinates to celestial coordinates are valid. These results are obtained in sidereal tracking,

but the astrometric accuracy changes depending on how long the stars are streaked. The greater the length of the star in the FoV the greater the error in the astro-referencing process. This effect is highlighted in Figure 53 that shows the accuracy in the astro-referentation for two images, one with 6.2 s of exposure time (on the left) and for one with 0.1 s (on the right).

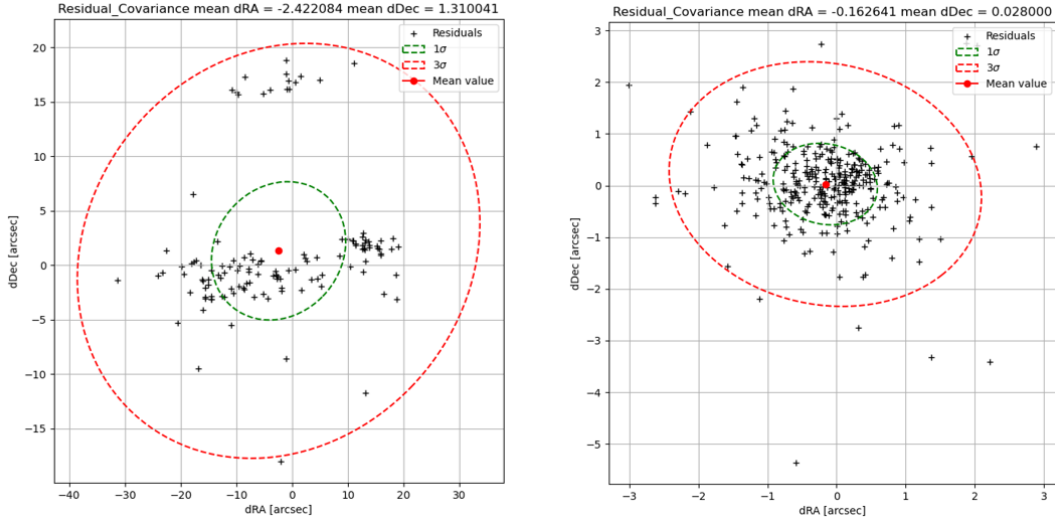


Figure 53. Accuracy in the stars position w.r.t. the stellar catalogue with FATE. On the left the stars are long stripes, while on the right are points.

5.7. Correlation with public catalogue

The correlation of a measurement, or a set of measurements, with a public catalogue such as NORAD's is the operation that permit to distinguish catalogued objects from unidentified ones. This process involves comparing observational data, such as the RA and Dec, with data stored in public catalogues. By identifying common parameters between the observed data and catalogue entries, it is possible to determine if the detected object is already known and catalogued, or if it represents a new, unlisted object.

This routine has been tested with data from surveys conducted by Sapienza observatories, within the IADC framework. For the implementation of the correlation of measurements from surveys in FATE, it will be required to have the complete list of TLEs for all objects in

the NORAD catalogue for each day of observation. In Figure 54 is shown the flow-chart for the correlation procedure.

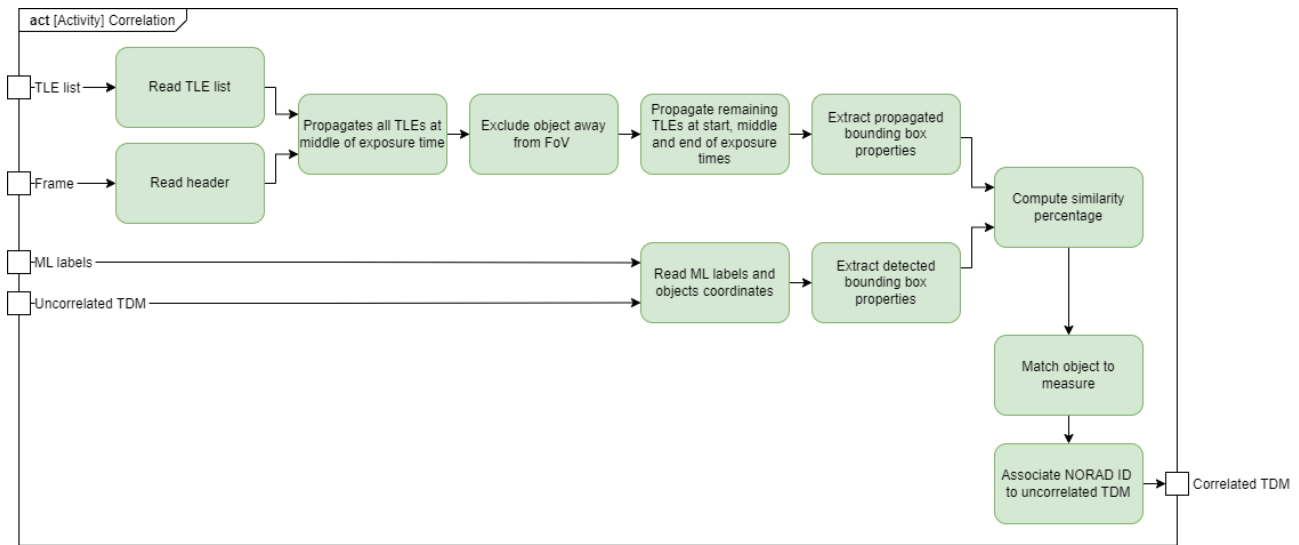


Figure 54. Correlation diagram

The process begins with measurements acquisition, where object detection is applied to all frames using the YOLO model. The properties of the bounding boxes, including the center coordinates (x, y) , positive and negative inclinations, diagonal, and confidence level, are saved. The centroids of the detected objects are then calculated. In the correlation procedure, the first step involves one-point propagation. From the frame's header, the center image's right ascension, declination, and exposure time are extracted. The NORAD catalogue is then propagated to the middle time. Next, catalogue pre-filtering is performed by excluding objects out of the field of view by comparing the angle between the lines of sight with a threshold radius of $\text{FoV}/2$ degrees around the center. In the three-points propagation step, the NORAD catalogue is propagated at the start, middle, and end times to determine the streak properties such as inclination (θ) , length (L) , and extremal points in (x, y) . All detections are then compared with all propagations, matching the detected inclinations, lengths and distance (D) with the propagated ones to assign a probability percentage. The correct object is assigned based on this probability. Finally, a visual inspection is shown in Figure 55 by projecting the results into the image.

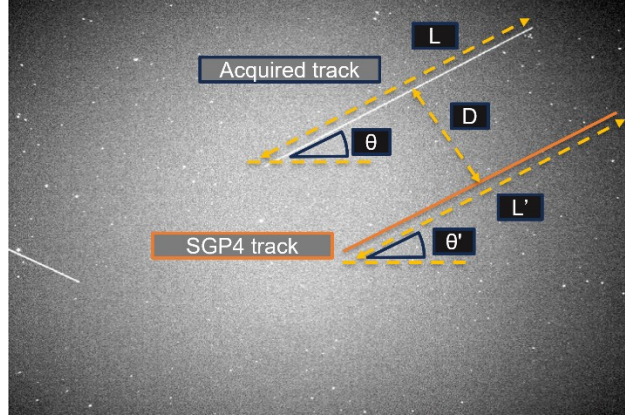


Figure 55. Comparison between propagated tracklet (orange) and the acquired one (white)

5.8. Light curve extraction

Performing aperture photometry for each object in each frame can be a computationally intensive task, particularly when dealing with large datasets consisting of thousands of frames. The computation involves identifying each object in the image and calculating its centroid and luminous flux using the chosen aperture size. This process must be repeated for every frame in the dataset. To manage the high volume of data generated by the AWARE observatory each night, the software must be designed to perform the aperture photometry quickly and efficiently. This requires the use of optimized algorithms and parallel processing techniques that can distribute the computation across multiple processors. Efficient management of the aperture photometry computation is crucial for enabling timely analysis of the astronomical data acquired by AWARE. Rapid and accurate measurement of the luminosity and centroid positions of celestial objects can facilitate the identification and characterization of astronomical objects, and analysis of variable objects such that undergoing changes in brightness. An example of the aperture photometry is shown in Figure 56 in which are represented the circle apertures adopted to estimate the object luminous flux.

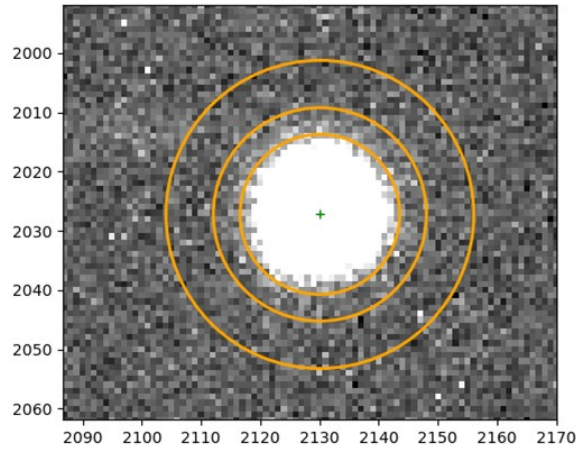


Figure 56. Aperture photometry circles applied to BEIDOU IGSO 4 object in TLE tracking mode

The circumference has a radius equal to the FWHM of the object and contains all the pixels that belong to the object. The circular ring is used instead for the estimation from the background necessary to correct the value of the luminous flux. This circular ring will have an internal radius a few pixels larger than the radius of the circumference and an external radius such that the area of the circular crown is at least 3 times greater than that of the object in order to have a better statistical representation of the background to subtract from the flow. The flux of the object is calculated in each frame thanks to aperture photometry and the set of all these flux values as a function of time represents the light curve of the object. In Figure 57 is shown the light curve of a passage of a BEIDOU IGSO 4 satellite but divided in four parts of the night. The point in red indicates the object flux value, and background, in that frame.

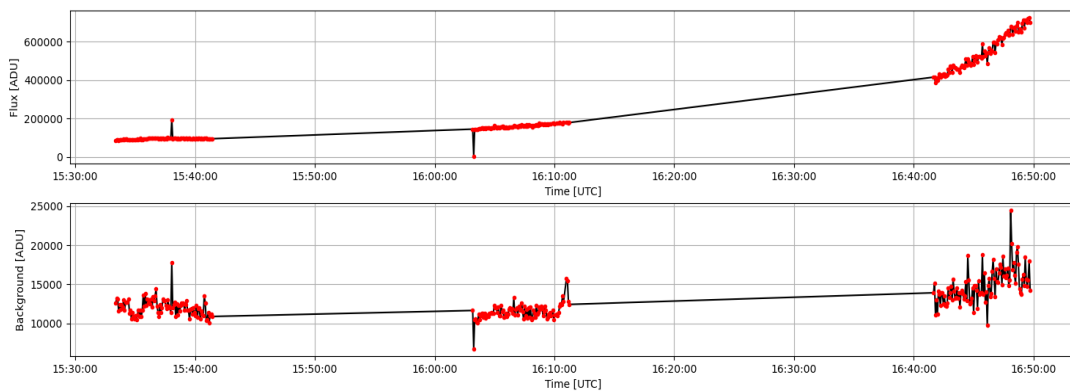


Figure 57 Example of the 37384 (Beidou 8) observation of 2022-11-15. In the upper part is reported the object flux over time, while in the bottom the estimated background

In this particular case, the satellite was observed at four different points during its passage across the sky, with increasing elevation. The FATE software calculates the luminous flux of the satellite at each point in time and the flux curve represents the variation of the satellite's brightness over time. In Figure 58 is presented a detail of the satellite at the different parts of the passage, which allows to visually inspect the satellite's brightness variations. This information can be used to analyse the behaviour of the satellite, identify any anomalies or unexpected variations in its brightness.

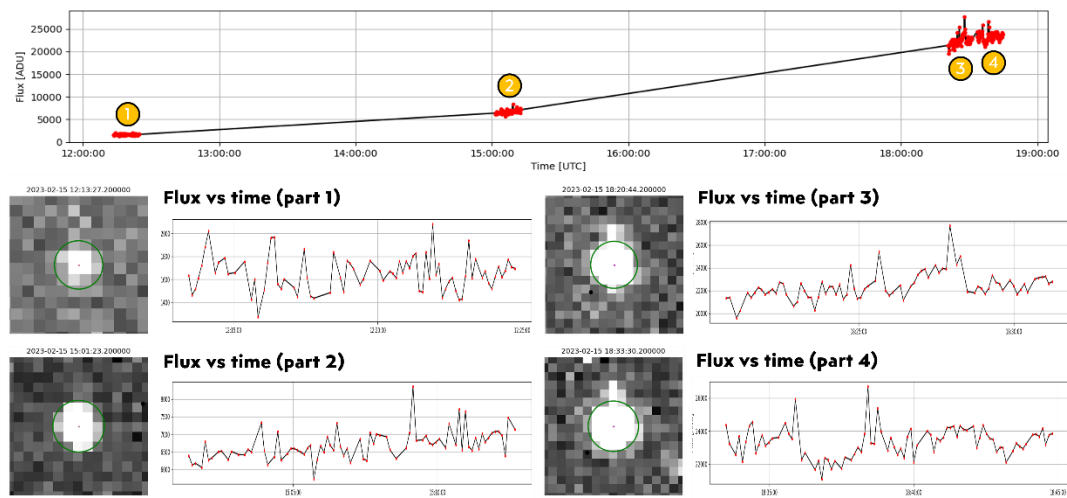


Figure 58. Example of flux versus time in different parts of the satellites passage

Photometric filters play a crucial role in astronomical observations, as they allow for the isolation of specific wavelengths of light, enabling detailed studies of celestial objects' properties, such as their composition, temperature, and distance. Observatories often use different filter systems depending on their specific requirements and objectives. The Sloan filter system (u, g, r, i, z) is designed for precision photometry and covers a wide spectral range with well-defined passbands, making it ideal for surveys and faint object detection. The Johnson-Cousins system (UBVRI), on the other hand, has been a standard for decades and is characterized by broader passbands, commonly used in general-purpose astronomical studies. In Figure 59 and Figure 60 shown two quasi-simultaneous multi-colours light curves of a geostationary object acquired with the two AWARE's acquisition system with the Sloan and Johnson photometric filter set.

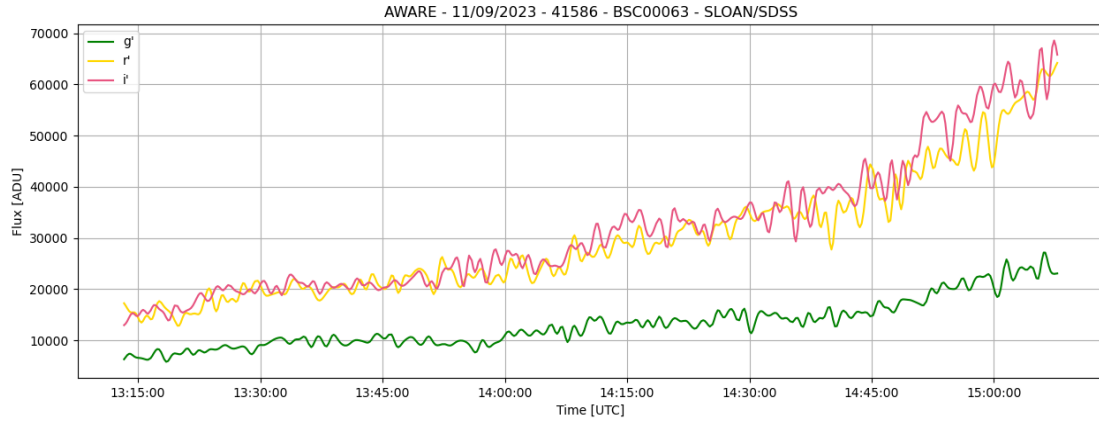


Figure 59. Balor Sloan acquisition

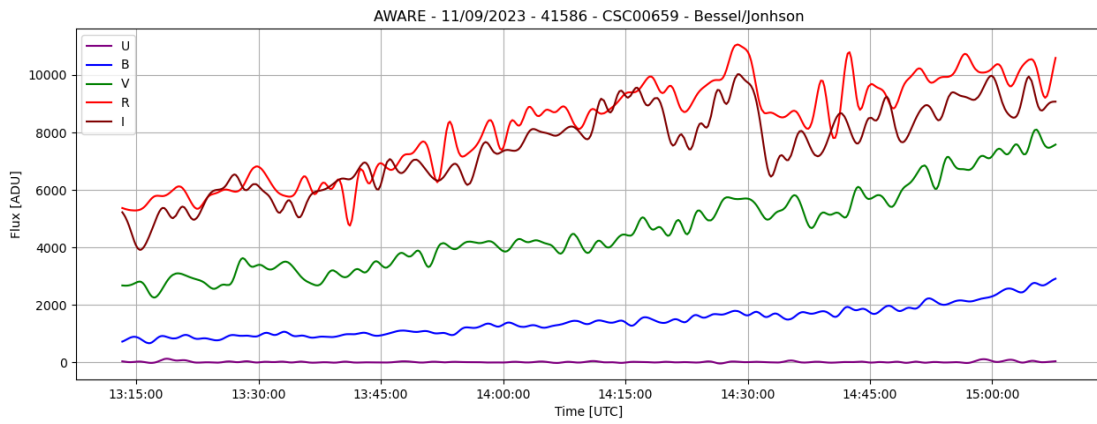


Figure 60. Marana Johnson acquisition

Unlike standard photometric filters, which are designed for precise measurements in specific wavelength ranges, RGB filters (red, green, blue) are primarily used for imaging purposes. These filters capture data across broad bands to produce visually representative images. The Mini-SURGE system consists of two digital cameras equipped with Bayer masks on their sensors. This configuration allows the extraction of flux from each individual channel simultaneously, providing real-time information across the RGB spectrum. In contrast, other systems typically use a filter wheel, which requires time to rotate between different filters, meaning the data from each channel is not acquired simultaneously. An example of RGB light curves of the same object but in different dates acquired by Mini-SURGE is shown in Figure 61.

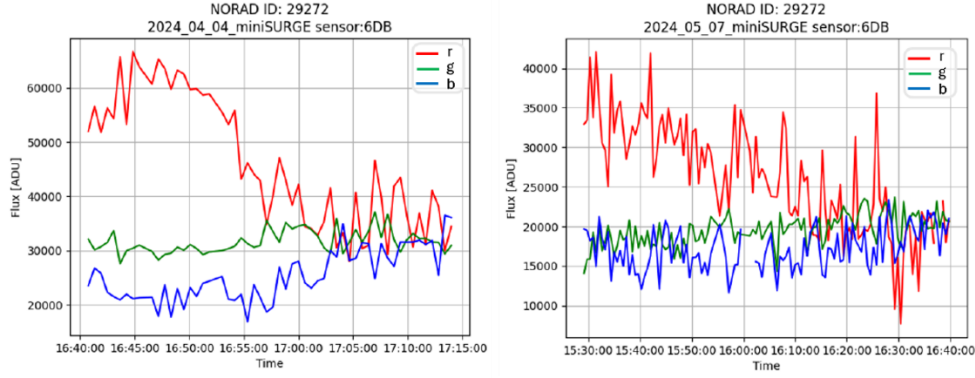


Figure 61. Mini-SURGE RGB light curves of object 29272 during two different dates

5.9. Time calibration

The time calibration is a crucial operation in the observatory's data processing pipeline that ensures the accuracy of the timestamp associated with each acquired frame. The accuracy of timestamps is crucial for correctly reconstructing the trajectory of objects and inaccurate timestamps can lead to significant errors in the analysis of the data. To perform the time calibration, FATE uses the public released ephemerides of some Global Navigation Satellite System (GNSS) and GEO satellite. The software then interpolates the ephemerides at the timestamp of the measurements and compares them with the acquired measurements, iteratively applying each time a different delta t until the norm of the residuals is minimized. The delta t represents the time bias in the system, and minimizing the residuals ensures that the timestamps are as accurate as possible. The flowchart of the time calibration procedure is shown in Figure 62.

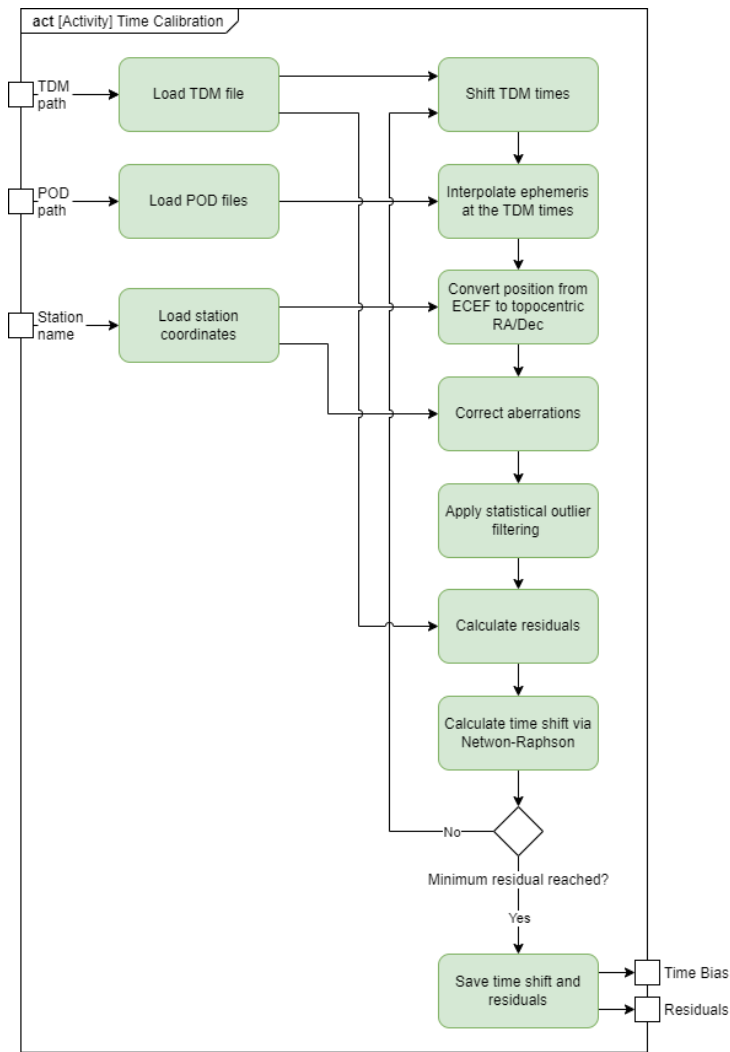


Figure 62. Time calibration diagram

The first operation that FATE performs is to check that the satellite is a calibration one, i.e. a satellite whose ephemeris are released. Once the check has been carried out, the ephemeris of the date of the observation are downloaded, if available. The inputs are the TDM of the observation, the ephemeris, and the Earth Orientation Parameters (EOP) at that date. In order to compare the TDM with the ephemeris, two main operations must be performed: the conversion of the reference system of the ephemeris and their interpolation. Then the RA, Dec contained in the TDM are compared with those of the ephemeris and an ellipsoid of covariance will be obtained in output, which represents the difference between the two. To find the time-bias, the operations described above are performed by translating the times of the TDM measurements until the minimum is reached for the average of the residuals between observations and ephemeris.

The ephemeris of satellites provides a list of positions that the satellite assumes at specific times. These positions are typically released every 5 seconds, which means that interpolation is needed to determine the satellite's position at intermediate times. FATE uses a Hermite interpolator for this purpose. Unlike Lagrange interpolation, which uses a set of points around the target time, Hermite interpolation incorporates both position and velocity data to provide a more accurate estimation. In the cases when velocity data is not provided directly, the method estimates it as the derivative of the position. This is particularly useful in the cases of geostationary satellites. An example of such interpolation is shown in Figure 63, where the ephemerides of a geostationary satellite, which does not release velocity data, are used and the velocity is calculated as the derivative of the position.

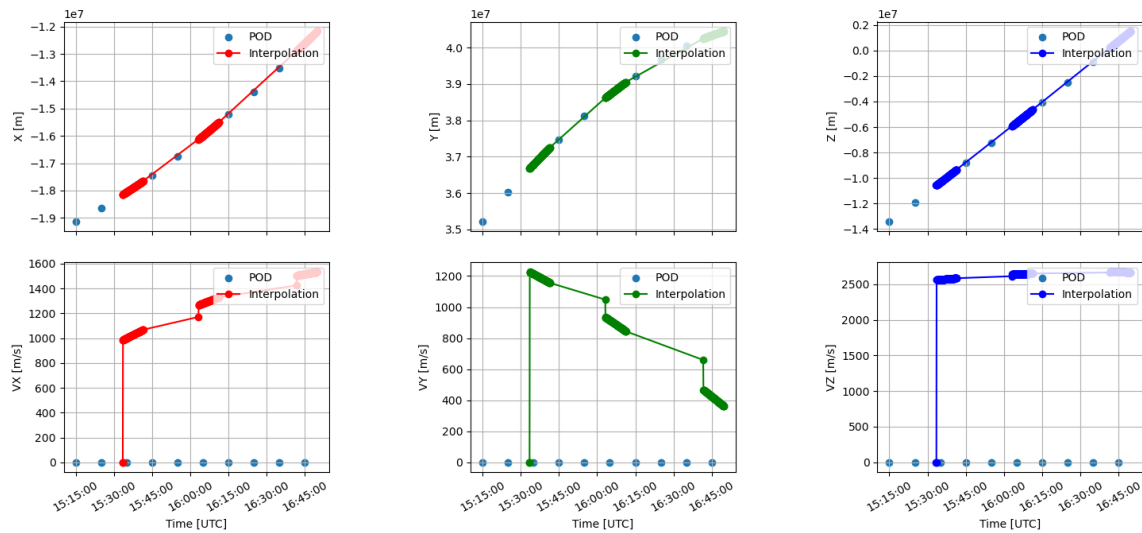


Figure 63 Example of ephemeris interpolation

In Figure 63 on the x-axis there is time, while on the y-axis there are X, Y, Z, Vx, Vy and Vz which the satellite assumes at a certain instant. The blue dots indicate the positions and velocity present in the ephemeris, while the coloured dots indicate the result of the interpolation with the Lagrange method. Straight lines are used only to connect the points of the interpolation.

The interpolated positions are then converted by the system providing the ephemeris into the ECI J2000 coordinate system for comparison with the TDM. The difference between the TDM and the ephemeris is assessed by adjusting the measurement times to determine the Δt that minimizes the norm of the residuals. For objects that do not provide ephemerides, measurements can be compared with their TLEs, though not for time calibration purposes. The comparison between the ephemerides and the measurements is shown in Figure 64, alongside a comparison with the TLE, offering a visual representation of the accuracy of the measurements. For this example, an observation with a time bias of 0.94 s was selected to highlight the effect of the time bias calibration procedure.

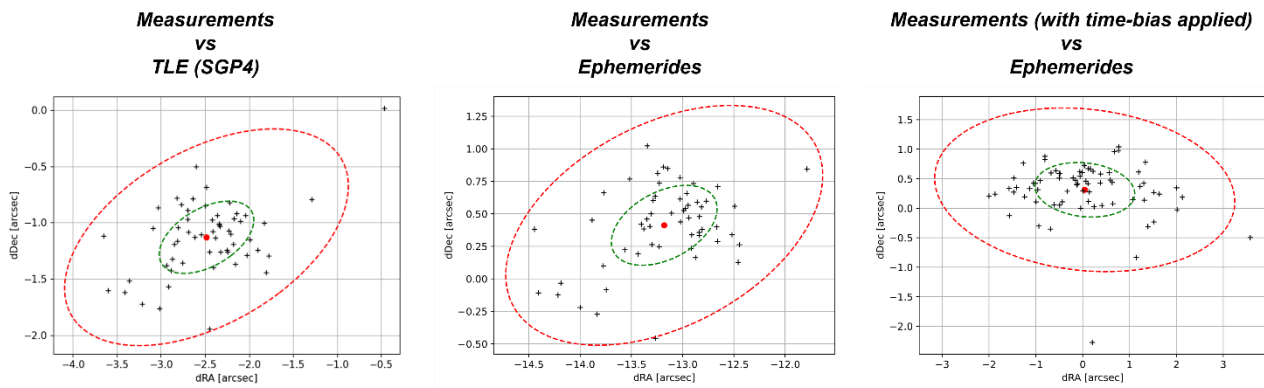


Figure 64. Example of comparison between measurements, TLE and ephemerides

Comparing real measurements with TLEs is not a simple task, as TLEs are based on averaged orbital parameters, while real measurements are derived from instantaneous observational data. TLEs represent a simplified model of the orbit, where the orbital parameters are averaged over time, and they do not account for short-term variations due to perturbations, in contrast, real measurements reflect the instantaneous position of the object. Therefore, the comparison between these two data sources can only provide an approximate order of magnitude estimate, helping to determine if the timestamp of the measurement is reasonable.

The time calibration and parameters were verified and confirmed via an observational campaign, during the span of several weeks. In particular, the validation of the routines for AWARE's time calibration took place during the validation and qualification campaigns of the ESA Expert Center. The analysis produced by FATE showed consistent and coherent

results with those produced by the ESA Expert Center, thus validating the results produced by FATE.

5.10. *IOD*

The challenge of Initial Orbit Determination (IOD) under the assumption of short arcs often does not yield a coherent solution with the true orbital parameters of the object due to limitations in the number of measurements, their temporal and spatial distribution, and the type of angular measurements, which hinder accurate parameter estimation. Since six independent quantities are required, at least three angles-only observations, that is six measurements, are needed to solve the IOD problem. However, some objects characterized by nearly circular orbits, can be treated as circular as a first approximation. In this case, the IOD problem consists of determining only four independent quantities, since the eccentricity is zero and the argument of the periapsis is not defined. Therefore, only two angles-only observations are required, that is four measurements.

The underlying principle for all angles-only IOD techniques is the use of topocentric angles (right ascension and declination or azimuth and elevation) to form Line-of-Sight (LoS) unit vectors. Figure 65 shows an example case for which an optical site provides angular data from multiple LoS vectors. Together with the knowledge of the observation site's position vector, the slant range of the observed body can be estimated using classical IOD methods, such as Laplace's, Gauss's or double-r iteration. According to Escobal, Laplace's method works best for interplanetary studies, while the double-r iteration method works best for Earth orbiting satellites. The latter is particularly effective for large spreads in the data, both in space (multiple observing locations) and in time (observations that are days apart). Instead, according to Long et al. [30], Gauss's method works best for interplanetary studies and works remarkably well when the data is separated by 10° or less.

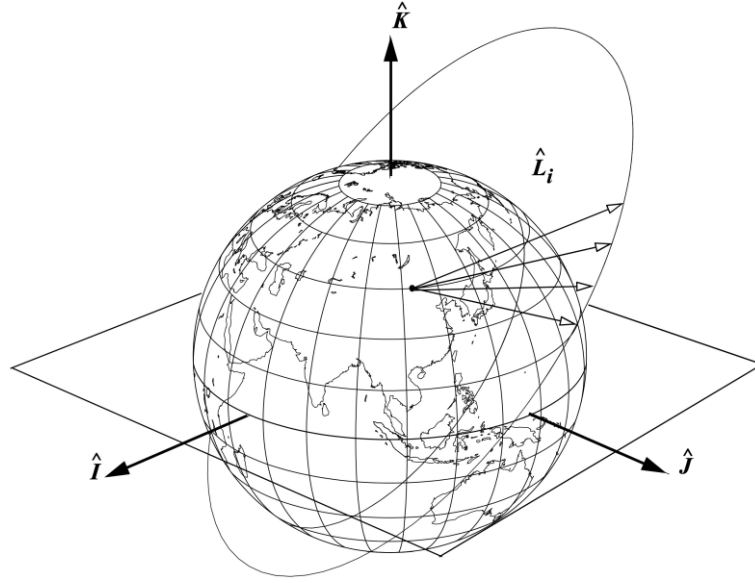


Figure 65: Geometry of angles-only observations [8]

For objects in GEO a circular orbit is a good approximation of the true orbit. Assume two observations of a GEO satellite are available, that is four measurements ordered as two pairs of RA and Dec $[(\alpha_1, \delta_1), (\alpha_2, \delta_2)]$ at times t_i . The first step is to form line-of-sight unit vectors, $\hat{L}_i$, to the satellite at each observation time.

$$\hat{L}_i = \begin{bmatrix} \cos \delta_i \cos \alpha_i \\ \cos \delta_i \sin \alpha_i \\ \sin \delta_i \end{bmatrix} : i = 1, 2 \quad (5)$$

If the slant range, ρ , to the satellite at each observation time was known, the position vectors of the satellite at times t_i could be easily computed as:

$$\bar{r}_i = \rho_i \hat{L}_i + \bar{r}_{site, ECI} \quad (6)$$

The dot product of (6) with itself yields an expression for the satellite's distance:

$$r = \sqrt{\rho^2 + 2\rho \hat{L} \cdot \bar{r}_{site} + \bar{r}_{site}^2} \quad (7)$$

However, since the slant range is unknown, it can be computed iteratively as follows. The circular orbit hypothesis entails that the satellite's distance is the same at all times:

$$r_1 = r_2 \quad \Leftrightarrow \quad r_1^2 = r_2^2 \quad (8)$$

Hence, given a reasonable guess of the satellite's slant range ρ_1 (e.g., $\rho_1^I \cong h_{GEO} = 35.786 \text{ km}$), the satellite's slant range ρ_2 can be computed solving (7) and (8):

$$\begin{cases} r_1^2 = r_2^2 \\ r^2 = \rho^2 + 2\rho\hat{L} \cdot \bar{r}_{site} + \bar{r}_{site}^2 \end{cases} \rightarrow r_1^2 = \rho_2^2 + 2\rho_2\hat{L}_2 \cdot \bar{r}_{site} + \bar{r}_{site}^2 \quad (9)$$

Solve equation 5.8 for the satellite's slant range ρ_2 to get:

$$\rho_2 = \frac{-2\hat{L}_2 \cdot \bar{r}_{site} + \sqrt{(2\hat{L}_2 \cdot \bar{r}_{site})^2 - 4(\bar{r}_{site}^2 - r_1^2)}}{2} \quad (10)$$

Consequently, the position vectors of the satellite at times t_i are known from (6) (i.e., $\bar{r}_1 = \rho_1^I\hat{L}_1 + \bar{r}_{site}$ and $\bar{r}_2 = \rho_2^I\hat{L}_2 + \bar{r}_{site}$) and the angle between them can be computed:

$$\Delta\theta : \cos \Delta\theta = \frac{x_{r1}x_{r2} + y_{r1}y_{r2} + z_{r1}z_{r2}}{|\bar{r}_1||\bar{r}_2|} \quad (11)$$

Given the interval of time, dt , between the two observations, the variation of the angle $\Delta\theta$ with time can be compared with the Earth's angular velocity, $\omega_\oplus$:

$$\frac{\Delta\theta}{dt} \triangleq \omega_\oplus = \sqrt{\frac{\mu_E}{r^3}} = 7,27 \cdot 10^{-5} \frac{rad}{s} \quad (12)$$

Depending on if $\frac{\Delta\theta}{dt} \geq \omega_\oplus$, the estimated guess of the satellite's slant range ρ_1 is respectively too low or too high. In this way, the slant range to the satellite at each observation time can be computed iteratively until the condition dictated by (12) is fulfilled. In Figure 66 is shown the activity diagram for the IOD procedure.

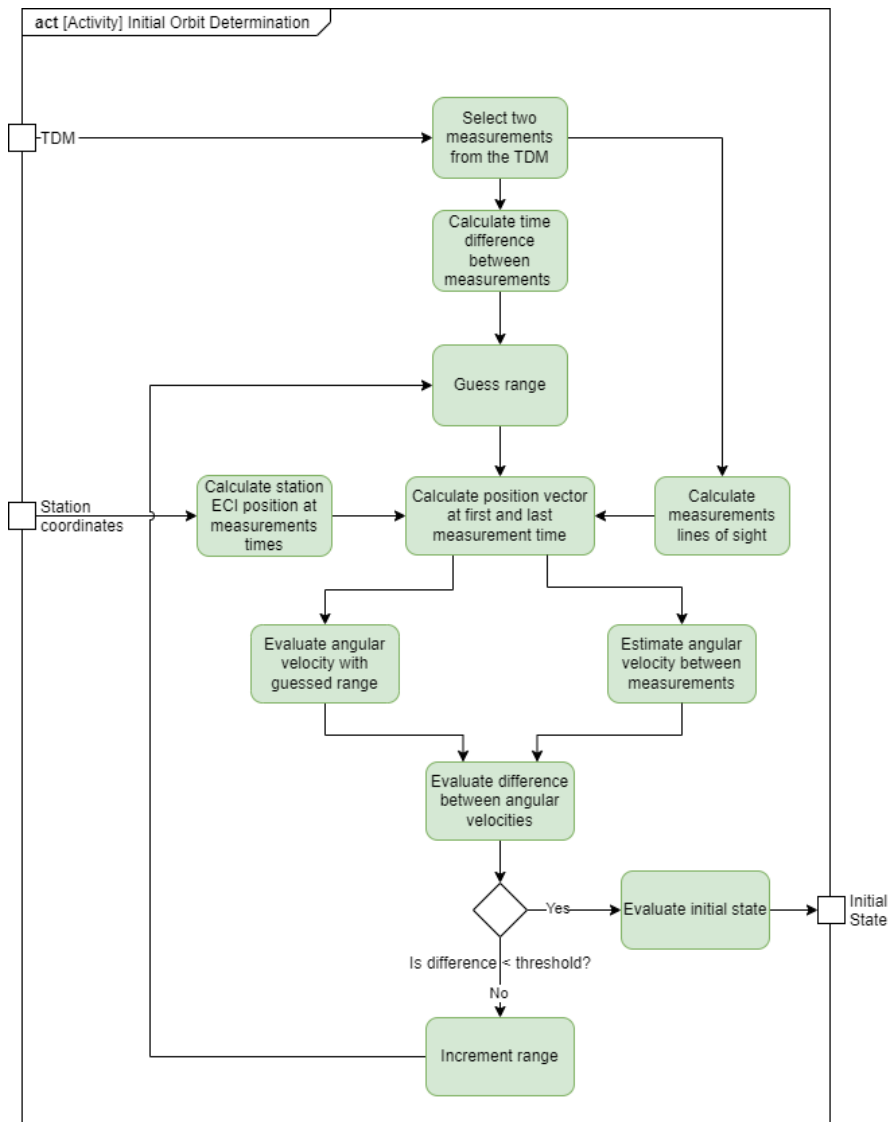


Figure 66. Initial orbit determination activity diagram

This simple method provides an initial estimate of the orbit (or, equivalently, of the state vector) under the assumption of a circular orbit. Even though this hypothesis is a good approximation for objects in GEO, a general orbit improvement process is still necessary to determine an accurate estimate of the object's state vector.

5.11. Orbit determination

The Orbit Determination (OD) problem consists of accurately determining the state vector for a body in motion in space. Once an initial estimate of the state vector has been computed, it can be improved using the complete batch of available observations. Over the years

multiple OD techniques and methods have been developed. Because these methods require iteration or incremental updates to the state, they are often referred to as differential correction [8]. The quantity and proximity of observations have a direct influence on the accuracy of OD techniques and a large number of sufficiently dense data is required to achieve a fulfilling result.

The process of orbit determination begins by loading the station coordinates and the TDM files that are then used in the IOD method, where an initial estimate of the satellite's orbit is generated. The resulting initial orbit state is saved for further refinement. To improve the accuracy of this initial estimate, a batch least-squares filter is applied, adjusting the orbit based on the discrepancies between the observed and predicted data. Once this step is completed, the refined orbital state is saved. Additionally, the planetary ephemeris is loaded to account for gravitational influences from other celestial bodies. With this data, the system numerically propagates the orbit, generating predictions for the satellite's future positions. Finally, the system creates an Orbit Ephemeris Message (OEM) file, which includes the satellite's trajectory information. The entire process is outlined in the diagram shown in Figure 67.

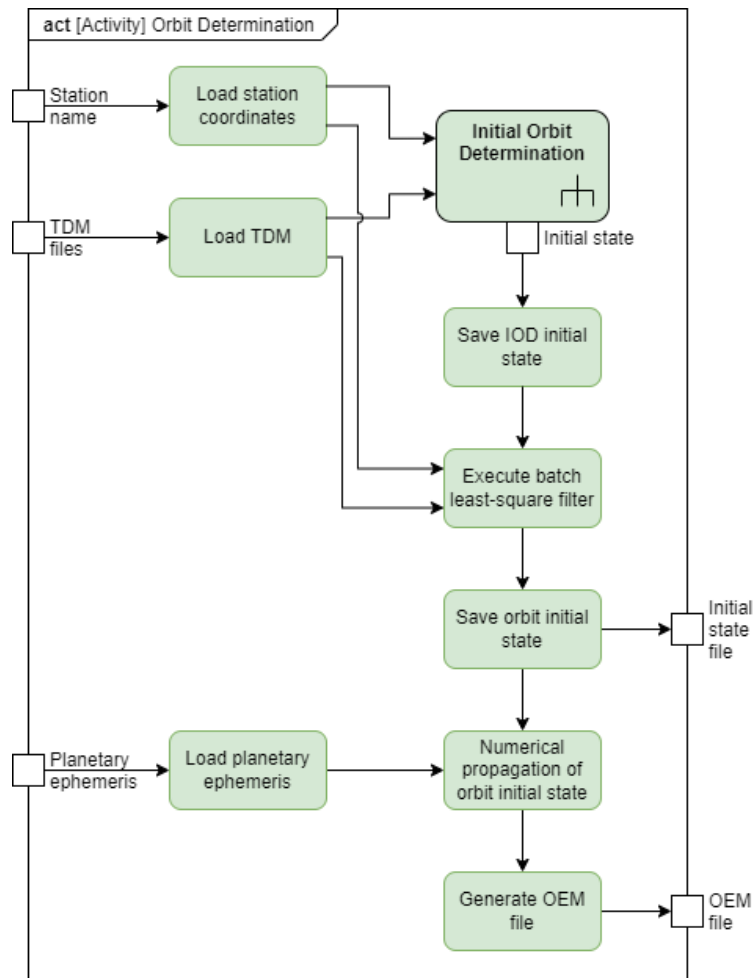


Figure 67. Orbit determination activity diagram

FATE employs the ESA/ESOC flight dynamics software GODOT for orbit determination, specifically leveraging its batch filter and numerical propagation capabilities. GODOT is a versatile tool designed for orbit-related computations, including orbit estimation, optimization, and analysis, with primary applications in mission analysis and in-flight operations. To enhance its functionality for space surveillance, additional features were integrated into GODOT within FATE to process data in RA and Dec, which are key observables in tracking. GODOT is widely used at ESOC for mission analysis and operations throughout the Solar System and is available under the ESA community license.

5.11.1. *Nonlinear least squares applied to optical observation*

In general, sequential-batch methods include linear least squares and nonlinear least squares. The linear least squares method is the simplest estimation technique. It assumes that the problem is linear, and it can be either unweighted or weighted. The former assumes that all data is given equal importance, whereas the latter permits to account for differences in the accuracy of measurements. Instead, the nonlinear least squares method can account for nonlinearities in the problem. An approximate solution can be determined by linearizing the problem and iterating to refine the answer. Least squares methods are essentially optimization problems whose objective is to minimize the sum of the squares of the residuals (hence the name least squares). The latter account for the difference between the model and the reality. The residuals, $\tilde{r}$, which are always indicated with the overtilde, are defined as the difference between observed, y_o , and computed, y_c , values of the dependent variable:

$$\tilde{r}_i = y_{o_i} - y_{c_i} \quad \text{at times } t_i \quad (13)$$

Given N observations, the least squares criterion (i.e., minimize the sum of the squares of the residuals) consists in determining the minimum of the cost function, J :

$$J = \sum_{i=1}^N \tilde{r}_i^2 = \text{minimum} \quad (14)$$

It should be noted that a squared function is used because a parabola ($\tilde{r}_i^2$) has a minimum whereas a line ($\tilde{r}_i$) does not. To find this minimum, the first derivative of J is set to zero.

The nonlinear least squares method is a powerful differential-correction technique that can accurately estimate an orbit's state from radar, optical, or other measurements. Assume an optical sensor can measure RA and Dec at each time, t_i , so that:

$$y_{o_i} = \begin{bmatrix} RA_o \\ Dec_o \end{bmatrix} \quad \text{at times } t_i \quad (15)$$

To calculate residuals, predicted measurements must be computed from the state vector:

$$y_{c_i} = \begin{bmatrix} RA_c \\ Dec_c \end{bmatrix} \quad \text{at times } t_i \quad (16)$$

Because y_{c_i} is a nonlinear function of the position and velocity vectors, the computed measurements can be expressed as a first-order Taylor-series expansion about the nominal trajectory y_{n_i} . If higher order terms are ignored, the vector expression at time $t = t_i$ is:

$$y_{c_i} = y_{n_i} + \Delta r_I \frac{\partial y_{n_i}}{\partial r_I} + \Delta r_J \frac{\partial y_{n_i}}{\partial r_J} + \Delta r_K \frac{\partial y_{n_i}}{\partial r_K} + \Delta v_I \frac{\partial y_{n_i}}{\partial v_I} + \Delta v_J \frac{\partial y_{n_i}}{\partial v_J} + \Delta v_K \frac{\partial y_{n_i}}{\partial v_K} \quad (17)$$

Hence, the residuals, $\tilde{r}_i$, can be computed using equation 5.12:

$$\tilde{r}_i = y_{o_i} - y_{c_i} = y_{o_i} - \left(y_{n_i} + \Delta r_I \frac{\partial y_{n_i}}{\partial r_I} + \dots + \Delta v_K \frac{\partial y_{n_i}}{\partial v_K} \right) \quad (18)$$

Assuming that each measurement is weighted using its appropriate standard deviation, the least-squares criterion can be applied to the weighted residuals:

$$J = \sum_{i=1}^N (w_i \tilde{r}_i)^T (w_i \tilde{r}_i) \quad (19)$$

Two vector equations, which produce six scalar equations, are obtained if the first derivatives of the cost function (eq. 5.18) are set equal to zero:

$$\sum_{i=1}^N w_i^T w_i \tilde{r}_i \frac{\partial \tilde{r}_i}{\partial \bar{r}} = 0 \quad (20)$$

Because $\frac{\partial \tilde{r}_i}{\partial r_I} = -\frac{\partial y_{n_i}}{\partial r_I}$, $\frac{\partial \tilde{r}_i}{\partial r_J} = -\frac{\partial y_{n_i}}{\partial r_J}$, etc., these equations can be put in matrix form:

$$- \begin{bmatrix} \frac{\partial y_{n_1}}{\partial r_I} & \frac{\partial y_{n_2}}{\partial r_I} & \dots & \frac{\partial y_{n_N}}{\partial r_I} \\ \frac{\partial y_{n_1}}{\partial r_J} & \frac{\partial y_{n_2}}{\partial r_J} & \dots & \frac{\partial y_{n_N}}{\partial r_J} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial y_{n_1}}{\partial v_K} & \frac{\partial y_{n_2}}{\partial v_K} & \dots & \frac{\partial y_{n_N}}{\partial v_K} \end{bmatrix} \begin{bmatrix} w_1^2 \tilde{r}_1 \\ w_2^2 \tilde{r}_2 \\ \vdots \\ w_N^2 \tilde{r}_N \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} \quad (21)$$

Define the left-hand partial-derivative matrix as $\bar{A}^T$ and the weighting matrix as $\bar{W}$:

$$\bar{A}^T \begin{bmatrix} w_1^2 \tilde{r}_1 \\ w_2^2 \tilde{r}_2 \\ \vdots \\ w_N^2 \tilde{r}_N \end{bmatrix} = \bar{A}^T \begin{bmatrix} w_1^T w_1 \tilde{r}_1 \\ w_2^T w_2 \tilde{r}_2 \\ \vdots \\ w_N^T w_N \tilde{r}_N \end{bmatrix} = \bar{A}^T \bar{W} \begin{bmatrix} \tilde{r}_1 \\ \tilde{r}_2 \\ \vdots \\ \tilde{r}_N \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} \quad (22)$$

where $\bar{A}^T$ is a $6 \times N$ matrix and $\bar{W}$ is an $N \times N$ matrix.

Substitute the definition of the residuals (18) and split the residual matrix to get:

$$\bar{A}^T \bar{W} \begin{bmatrix} y_{o_1} - \left(y_{n_1} + \Delta r_I \frac{\partial y_{n_1}}{\partial r_I} + \dots + \Delta v_K \frac{\partial y_{n_1}}{\partial v_K} \right) \\ y_{o_2} - \left(y_{n_2} + \Delta r_I \frac{\partial y_{n_2}}{\partial r_I} + \dots + \Delta v_K \frac{\partial y_{n_2}}{\partial v_K} \right) \\ \vdots \\ y_{o_N} - \left(y_{n_N} + \Delta r_I \frac{\partial y_{n_N}}{\partial r_I} + \dots + \Delta v_K \frac{\partial y_{n_N}}{\partial v_K} \right) \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} \quad (23)$$

$$\bar{A}^T \bar{W} \begin{bmatrix} y_{o_1} - y_{n_1} \\ y_{o_2} - y_{n_2} \\ \vdots \\ y_{o_N} - y_{n_N} \end{bmatrix} - \bar{A}^T \bar{W} \begin{bmatrix} \Delta r_I \frac{\partial y_{n_1}}{\partial r_I} + \dots + \Delta v_K \frac{\partial y_{n_1}}{\partial v_K} \\ \Delta r_I \frac{\partial y_{n_2}}{\partial r_I} + \dots + \Delta v_K \frac{\partial y_{n_2}}{\partial v_K} \\ \vdots \\ \Delta r_I \frac{\partial y_{n_N}}{\partial r_I} + \dots + \Delta v_K \frac{\partial y_{n_N}}{\partial v_K} \end{bmatrix} = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

Define the observation matrix, $\bar{b}$, as the difference between the observed and the nominal trajectory ($N \times 1$ vector) and the correction to the state vector as $\delta \bar{X}$ ($N \times 1$ vector):

$$\bar{A}^T \bar{W} \bar{b} = \bar{A}^T \bar{W} \bar{A} \delta \bar{X} \quad (24)$$

Equations (24) are called the normal equations. Although $\bar{A}$ and $\bar{A}^T$ usually are not square matrices, the matrix product $\bar{A}^T \bar{W} \bar{A}$ is always square. Thus, assuming that $\bar{A}^T \bar{W} \bar{A}$ is invertible, provided it is positive definite (not singular), the differential correction equation for nonlinear weighted least squares is:

$$\delta \bar{X} = (\bar{A}^T \bar{W} \bar{A})^{-1} \bar{A}^T \bar{W} \bar{b} = \bar{P} \bar{A}^T \bar{W} \bar{b} \quad (25)$$

where $\bar{A}^T \bar{W} \bar{A}$ is the information matrix and $\bar{P} = (\bar{A}^T \bar{W} \bar{A})^{-1}$ is the covariance matrix. The covariance matrix contains the variances and covariances of the solution parameters (state space) and indicates observability from the available data types, as well as the effect of noisy data on the estimated parameters. These statistical values will be accurate only if the chosen dynamical model, which depends on the understanding of the physics of the problem, matches reality and the calibration values are correct. The diagonal terms of the covariance matrix are the variances of the estimate of the state parameters. The square roots of the variances are the sample standard deviations for each element of the state vector. These values establish a level of uncertainty in each element of the state vector. Instead, the off-diagonal elements are called covariance terms, and they contain the correlation coefficients. These coefficients represent the degree of correlation among the elements, with zero being no correlation. Positive signs indicate a direct correlation, while negative signs imply an inverse relationship. Finally, the state vector can be corrected using (25):

$$\bar{X} = \bar{X} + \delta \bar{X} \quad (26)$$

The main difficulty when building a differential correction software is the computation of the partial-derivative matrix, which is essential to compute equation (25). In general, both

analytical and numerical techniques can be used to compute this matrix. The partial-derivative matrix, $\bar{\bar{A}}$, describes how changes in the initial state (position and velocity vectors) affect the predicted measurements (computed). To find the nonlinear time-dependent derivatives the first step is to break up the partial derivative using the chain rule:

$$\bar{\bar{A}} = \frac{\partial \text{observations}}{\partial \bar{X}_o} = \frac{\partial \text{observations}}{\partial \bar{X}} \frac{\partial \bar{X}}{\partial \bar{X}_o} = \bar{\bar{H}} \bar{\bar{\phi}} \quad (27)$$

Equation (27) distinguishes the observation partial-derivatives ($\bar{\bar{H}}$) from the partial-derivative of the state over time ($\bar{\bar{\phi}}$). The latter is called the matrix of variational equations, or the error state transition matrix. This matrix relates the state errors from t to t_0 . Both matrices can be computed by finite differencing or using analytical or by numerical integration techniques. The partial-derivative matrix can be approximated by finite differencing. This technique consists in taking small differences of the state to determine their effect on the system.

$$\bar{\bar{A}} = \frac{\partial \text{observations}}{\partial \bar{X}_o} \cong \frac{f(\bar{X} + \delta_i) - f(\bar{X})}{\delta_i} \quad (28)$$

The nominal state at epoch is used to generate position and velocity vectors at the times of the observations. Six additional trajectories are determined as each component of the position and velocity vectors is changed. The partial derivative of the observations (at the observation times) can be approximated by using the observations found from the nominal trajectory and one of the varied trajectories. It's best to modify each state element with a percentage of the vector magnitude rather than a fixed delta or a percentage of each element when using position and velocity vectors in the state vector. This technique eliminates the sensitivity to large and small values within the state vector elements.

Another approach is central differencing, which takes in account both positive and negative deviations from the nominal state vector to determine the approximation.

$$\bar{A} = \frac{\partial \text{observations}}{\partial \bar{X}_o} \cong \frac{f(\bar{X} + \delta_i) - f(\bar{X} - \delta_i)}{2\delta_i} \quad (29)$$

This method ensures a more accurate estimate of the derivative at the desired time but requires more computational time because twelve trajectories are required.

5.11.2. *Analysis of One-Pass, Two-Pass, and Multi-Day Observation*

For the analysis of One-Pass, Two-Pass, and Multi-Day observation, the LEO satellite Lares (NORAD ID: 38077) was selected as the target object. Lares follows a nearly circular orbit with a semi-major axis of approximately 7828 km and an inclination of about 69.5°, characteristics that make it a suitable object for tracking and orbit determination in LEO. The observations were acquired by the AWARE observatory over two days, 2024-05-06 and 2024-05-07, and the integration time span for comparing the estimated orbit from the OD procedure with the ephemerides extended from 2024-05-05T23:59:59.000 to 2024-05-09T19:39:01.000 (UTC), as ephemerides were available for this period. Measurement noise was set to 5 arcseconds, and the position error on the initial state for the BLS filter was set to 20 km for all the cases. The IOD process was performed using the two-point circular method, as previously described, to derive the initial state for the BLS filter. This method was applied consistently across all scenarios to ensure uniformity in the analysis and comparison of results.

The analysis investigated three distinct scenarios to assess how the accuracy of orbit determination varies depending on the number of observation passes.

- Single observation pass (2024-05-06): Data from a single pass on 2024-05-06 provided 39 observables, collected between 12:32:49.235558 and 12:34:53.567965 (UTC).
- Double observation passes (2024-05-07): On 2024-05-07, two separate passes were observed. The first pass, from 11:29:44.952095 to 11:34:32.111676 (UTC), yielded 119

observables, while the second pass, from 13:29:55.113847 to 13:35:31.067161 (UTC), provided an additional 28 observables.

- Combined data from both dates: Observations from both dates (2024-05-06 and 2024-05-07) were combined, resulting in a total of 186 observables.

The details about the data are shown in Table 7.

Table 7. Acquired data for Lares satellite (NORAD ID: 38077)

TDM 1	
Number of observables	39
Start epoch [UTC]	2024-05-06T12:32:49.235558
End epoch [UTC]	2024-05-06T12:34:53.567965
TDM 2	
Number of observables	119
Start epoch [UTC]	2024-05-07T11:29:44.952095
End epoch [UTC]	2024-05-07T11:34:32.111676
TDM 3	
Number of observables	28
Start epoch [UTC]	2024-05-07T13:29:55.113847
End epoch [UTC]	2024-05-07T13:35:31.067161

- One pass case

For the first case, the analysis utilized only the initial set of observables acquired during the pass on 2024-05-06. The IOD and OD procedures were conducted in the ICRF reference system, with an initial condition epoch of 2024-05-06T12:32:49.235558 (UTC). The OD procedure converged after two iterations, and the comparison of the IOD and OD states revealed slight refinements in both the position and velocity vectors compared to the initial IOD values as shown in Table 8.

Table 8. Comparison between IOD and OD initial state

	IOD	OD
--	-----	----

X, Y, Z [km]	[-4243.181649, 2980.360250, -5868.639409]	[-4242.565663, 2981.154793, -5869.928383]
VX, VY, VZ [km/s]	[-5.880811, -0.473995, 4.011266]	[-5.882763, -0.479428, 4.01833]

Figure 68 and Figure 69 show the position error in the ICRF reference frame for the estimated orbit over a period of four days and one day, respectively.

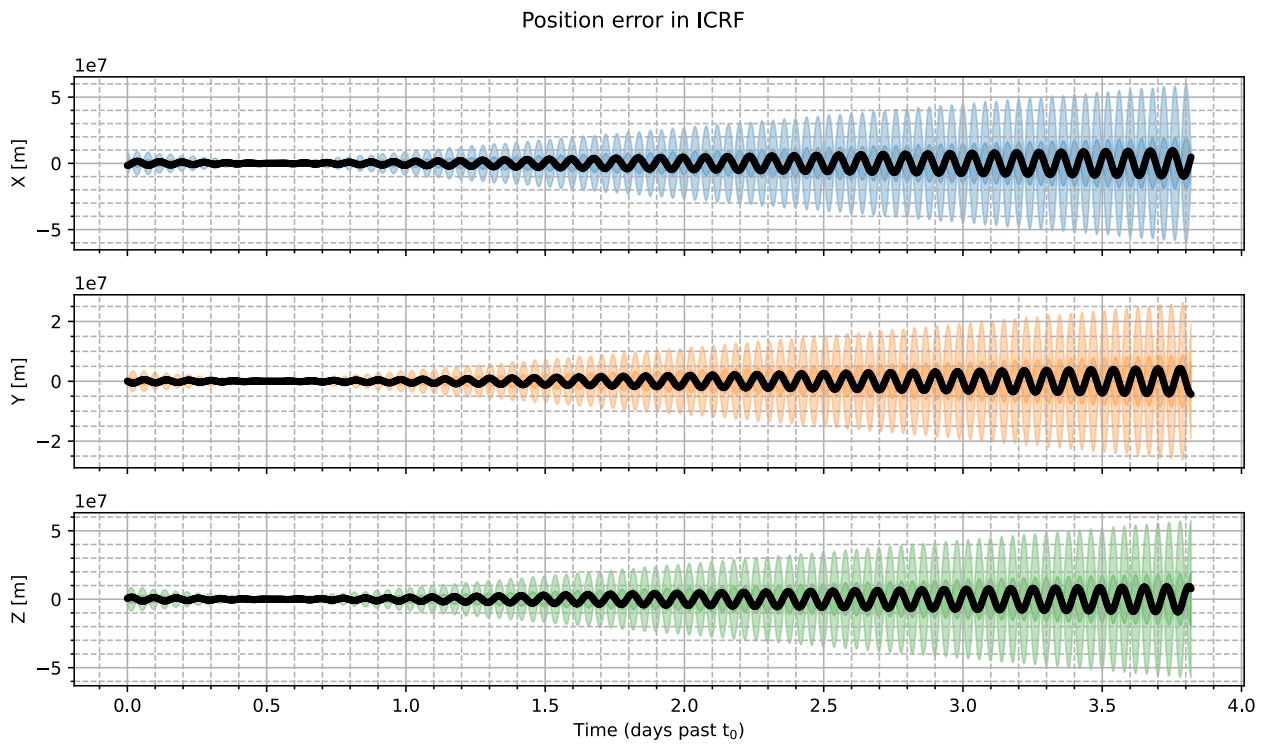


Figure 68. Comparison of the position cartesian components between the estimated orbit and the ephemerides over 4 days

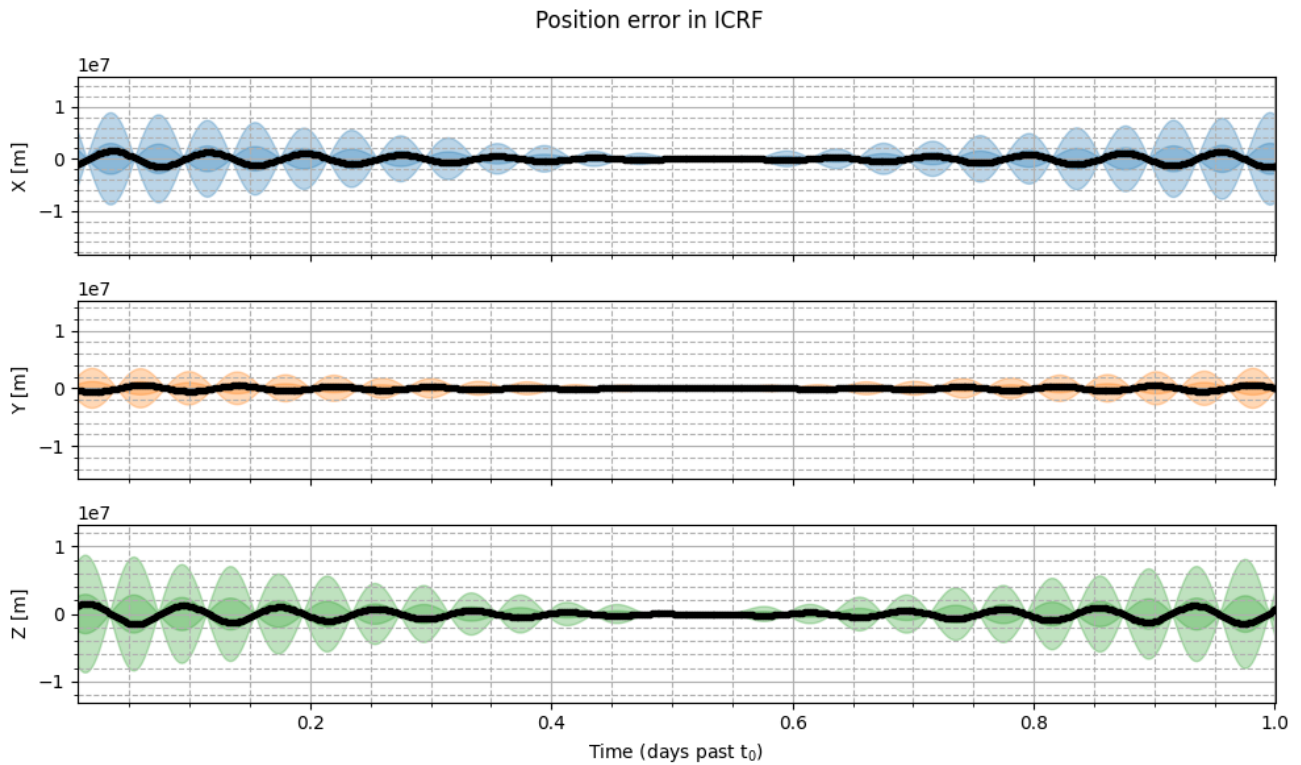


Figure 69. Comparison of the position cartesian components between the estimated orbit and the ephemerides over 1 day

- Two-pass case

For the second case, the analysis incorporated two sets of observables acquired on 2024-05-07, corresponding to two distinct passes. The IOD and OD procedures have the initial condition epoch set to the start of the first observable from 2024-05-07T11:29:44.952095 (UTC). The inclusion of an additional pass provided a more extensive dataset, enabling the OD process to converge in 4 iterations with improved accuracy in the estimated orbital parameters as shown in Table 9, Figure 70 and Figure 71.

Table 9. Initial condition IOD and OD in ICRF reference system at 2024-05-07T11:29:44.952095 [UTC]

	IOD	OD
X, Y, Z [km]	[-4041.737557, 3103.225066, -5943.835608]	[-4041.998743, 3103.013332, -5942.885318]
VX, VY, VZ [km/s]	[-5.959280, -0.261935, 3.915485]	[-5.951645, -0.264354, 3.918742]

The comparison of the OD with respect to the ephemerides highlights further refinements in both position and velocity vectors, demonstrating the positive impact of additional observation data on the accuracy of the orbit determination.

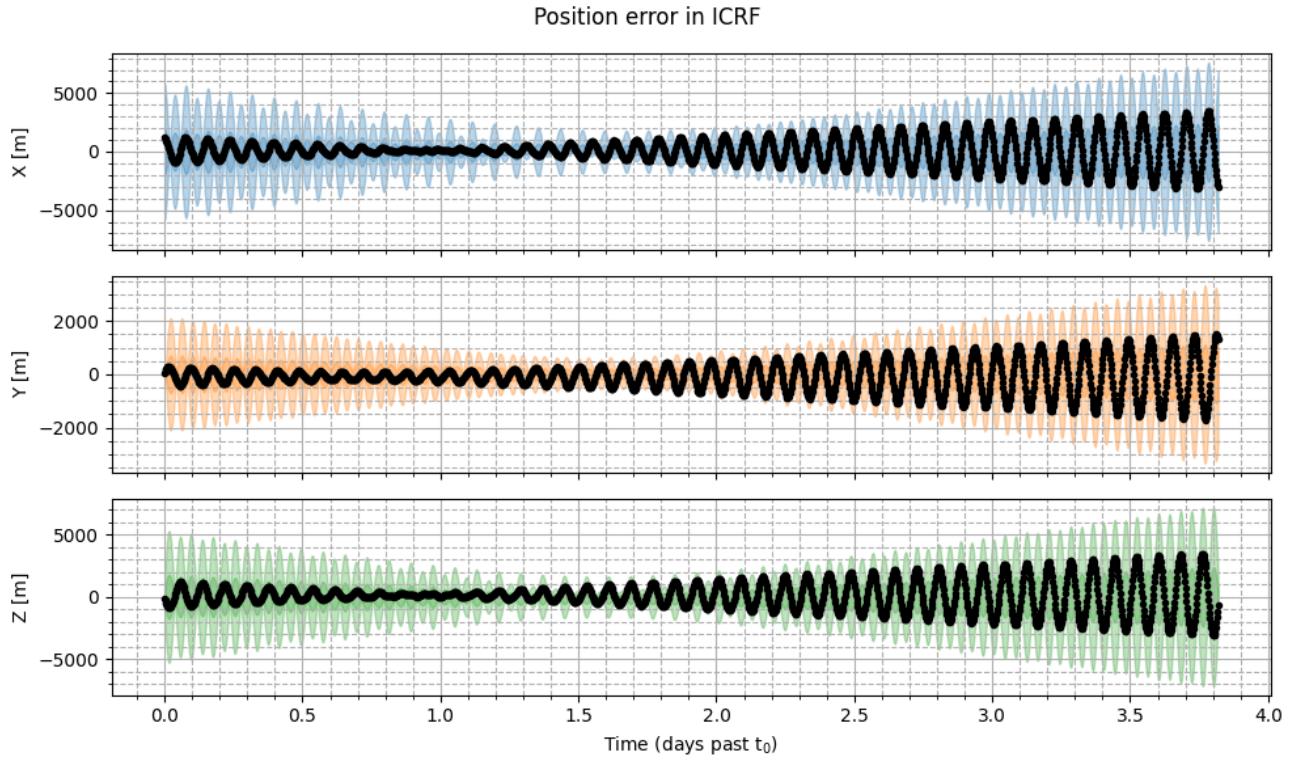


Figure 70. Comparison of the position cartesian components between the estimated orbit and the ephemerides over 4 days

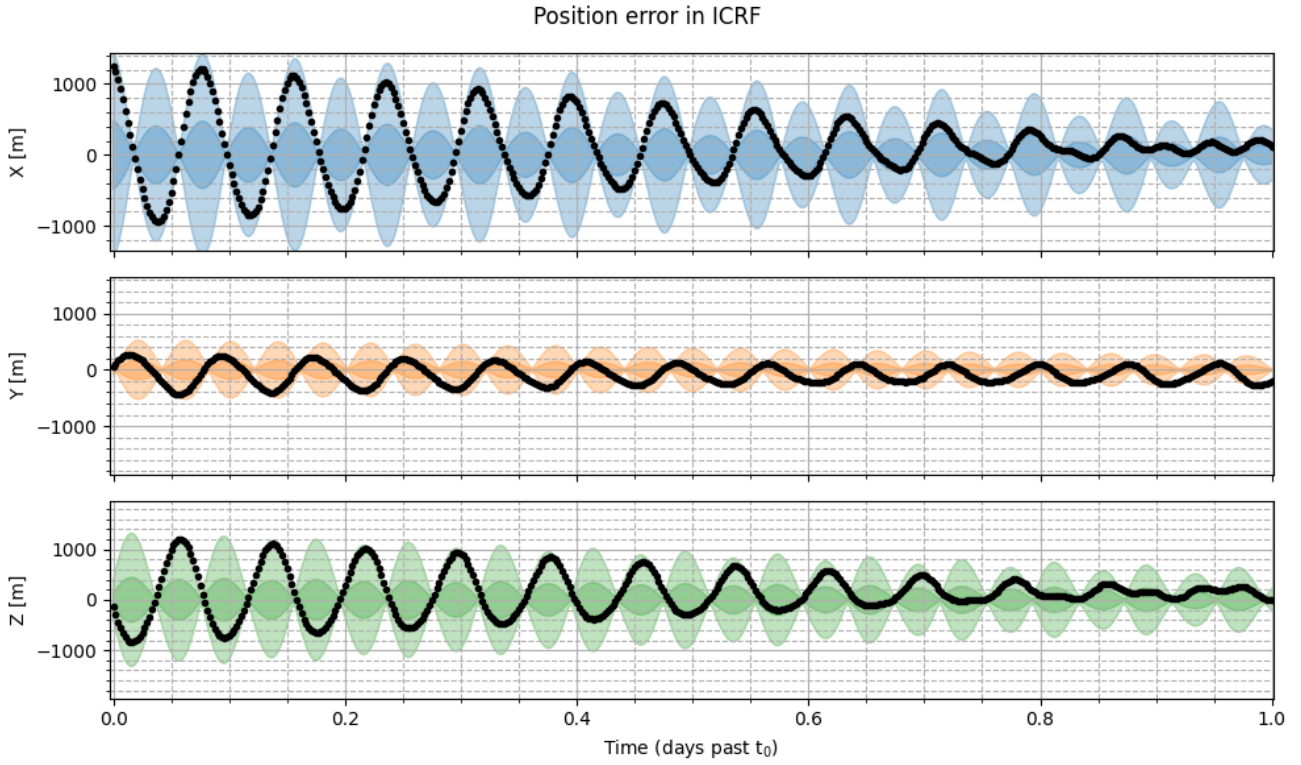


Figure 71. Comparison of the position cartesian components between the estimated orbit and the ephemerides over 1 day

- Multi-day case

For the third case, the analysis considered the complete dataset, combining the observations acquired on 2024-05-06 and 2024-05-07. The IOD and OD processes were conducted with the initial condition epoch set to 2024-05-06T12:32:49.235558 (UTC), corresponding to the start of the first pass of the second day. In Table 10 are shown the states obtained with the IOD and OD procedures.

Table 10. IOD/OD Initial conditions in ICRF reference system at 2024-05-07T11:29:44.952095 [UTC]

	IOD	OD
X, Y, Z [km]	[-4041.737557, 3103.225066, -5943.835608]	[-4041.995250, 3103.016101, -5942.839350]
VX, VY, VZ [km/s]	[-5.959280, -0.261935, 3.915485]	[-5.951664, -0.264387, 3.918778]

Utilizing data from multiple passes over two days allowed for a significantly enhanced orbital determination, as the increased volume of observations provided better constraints on

the orbital model. The comparison in Figure 72 and in Figure 73 demonstrates substantial refinements in both position and velocity vectors compared to the previous cases, underscoring the benefits of combining multiple observation sets for achieving higher accuracy in orbit determination.

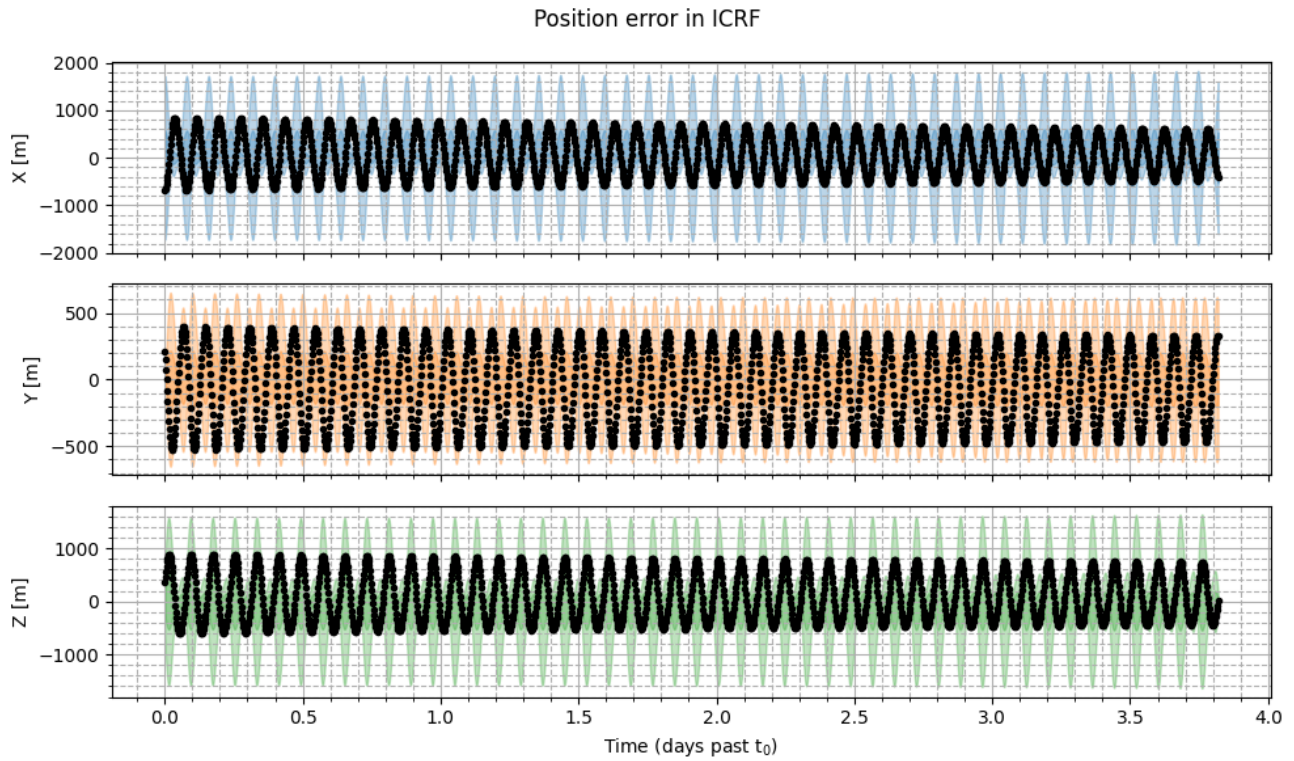


Figure 72. Position errors in x , y , z in ICRF reference system

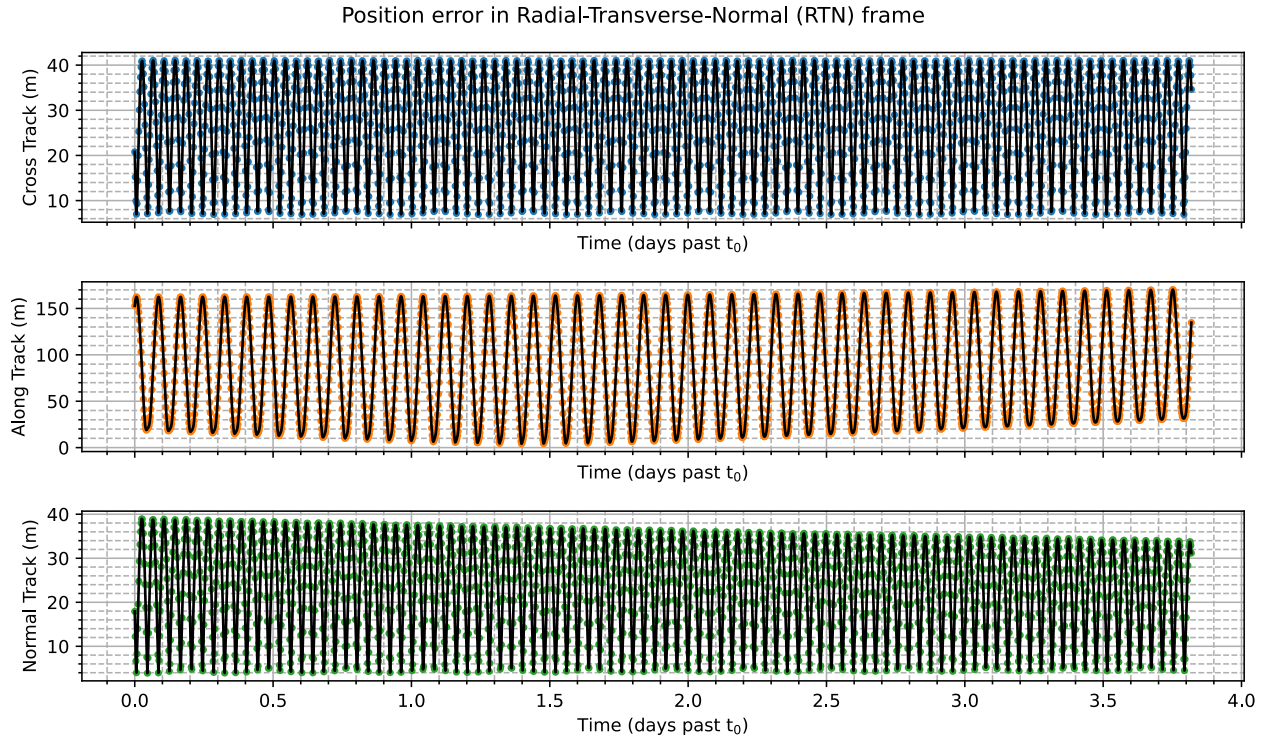


Figure 73. Errors along x,y,z in the RTN reference frame

In Table 11, the orbital parameters obtained for three different orbit determination (OD) cases are presented. Among the three cases, OD case 3 demonstrates the most accurate and consistent results, particularly in terms of the semimajor axis and eccentricity, which are very close to expected values.

Table 11. COE comparison for the 3 different cases

COE	OD case 1	OD case 2	OD case 3
Semimajor axis [km]	7846.187819	7817.910624	7817.921445
Eccentricity	0.002072	0.001641	0.001637
Inclination [deg]	69.514787	69.514345	69.514133
RAAN [deg]	169.924364	168.317270	168.317326
Argument of perigee [deg]	337.294368	91.025692	90.866803
True anomaly [deg]	329.569929	214.840203	214.999234

5.11.3. Multiple observatory case

Before the multi-site orbit determination, is presented the orbit determination for a Molniya object, COSMOS 1541 (NORAD ID: 14790), observed during an extended period to verify the OD procedure for an eccentric orbit. The observation starts from 2024-11-17T18:40:03.933 to 2024-11-17T22:10:35.875 UTC, during which 284 measurements were acquired. In Figure 74 is shown the observed part of the object trajectory.

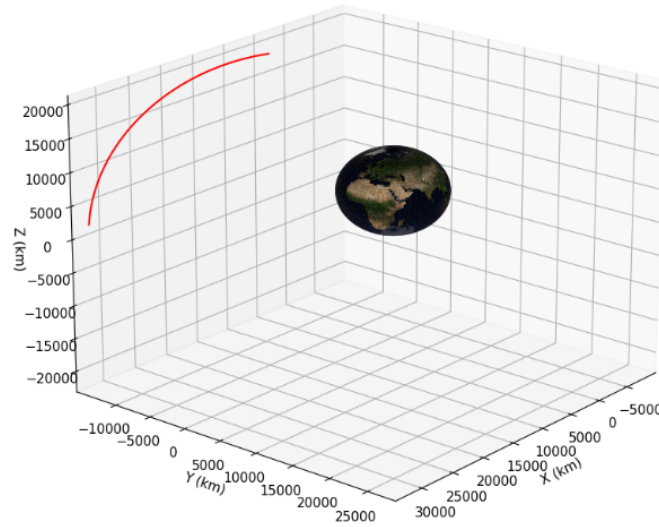


Figure 74. Observed trajectory of the Molniya object from SCUDO observatory

The observation mode was sidereal tracking, causing the object to appear as streaks in the images. The observation presented several challenges: the near-full Moon created a bright sky background, the object was dim with an approximate magnitude of 12, and it exhibited tumbling motion, resulting in discontinuous streaks across many frames. This tumbling also made centroid calculation imprecise. To address this, a binning mode of 3 was used, increasing the dwell time of the object on each pixel and yielding a pixel scale of approximately 6 arcseconds per pixel. Despite these adjustments, a centroiding error of about 3 pixels was assumed, corresponding to a positional error of 15 arcseconds. For the IOD, given the highly eccentric orbit of the object, the classical three-point Gauss method was employed instead of a circular approximation. This case was analyzed to assess the effectiveness of the OD process when applied to eccentric orbits under challenging observational conditions.

In Figure 75, the trajectory obtained using the OD procedure is shown. Figure 76 presents the position error between the OD results and the TLE at the times of observation. Additionally, Figure 77 displays a similar graph, but the comparison spans a period starting 6 hours before the first measurement and extending 6 hours after the last one.

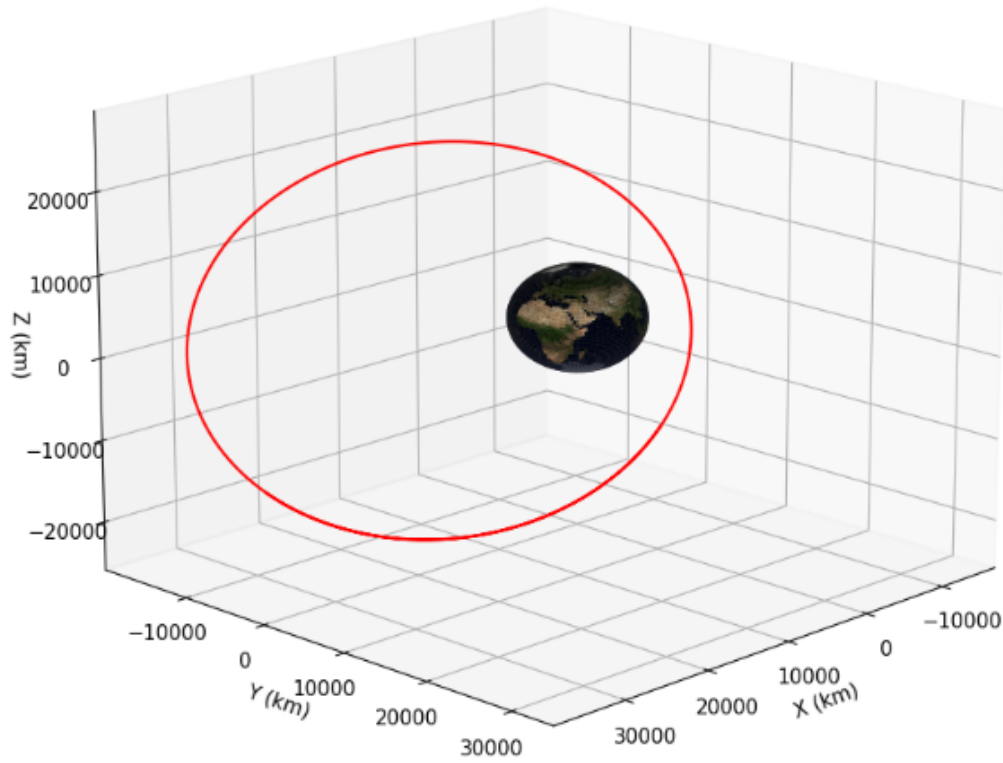


Figure 75. Estimated trajectory with OD procedure for the Molniya case

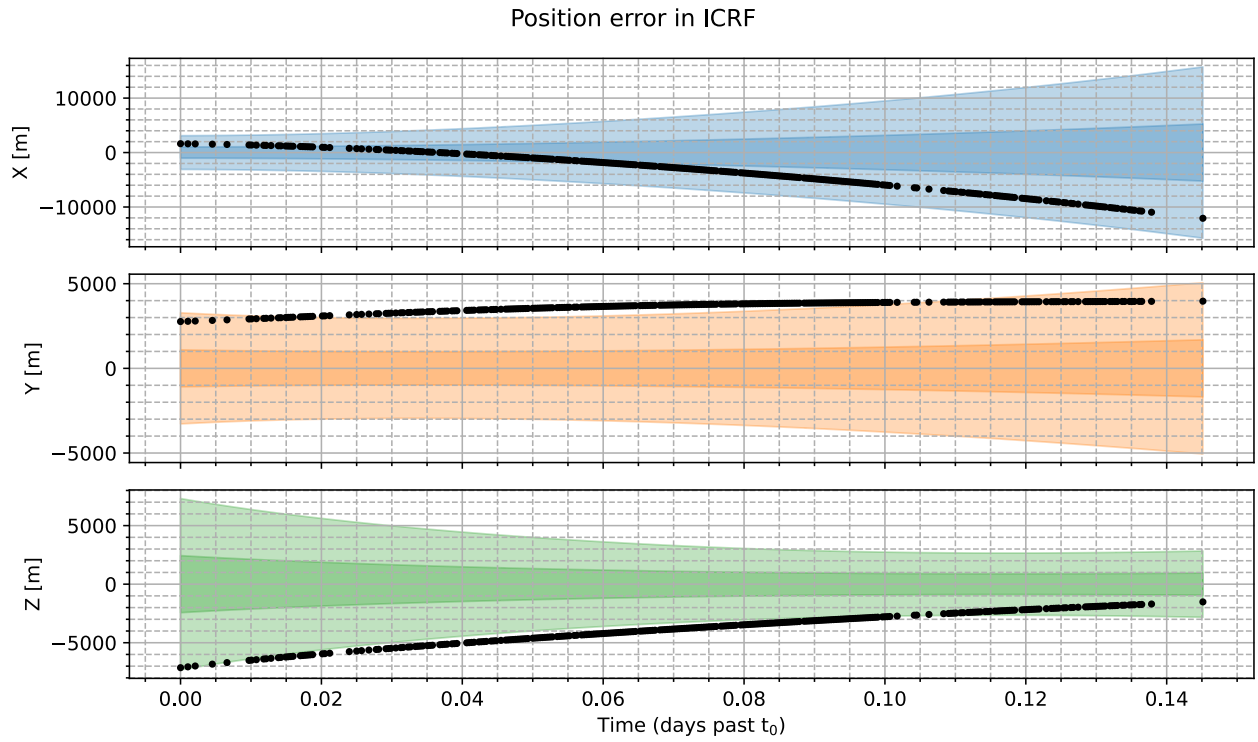


Figure 76. Position error of the OD with respect to the TLE at observation times

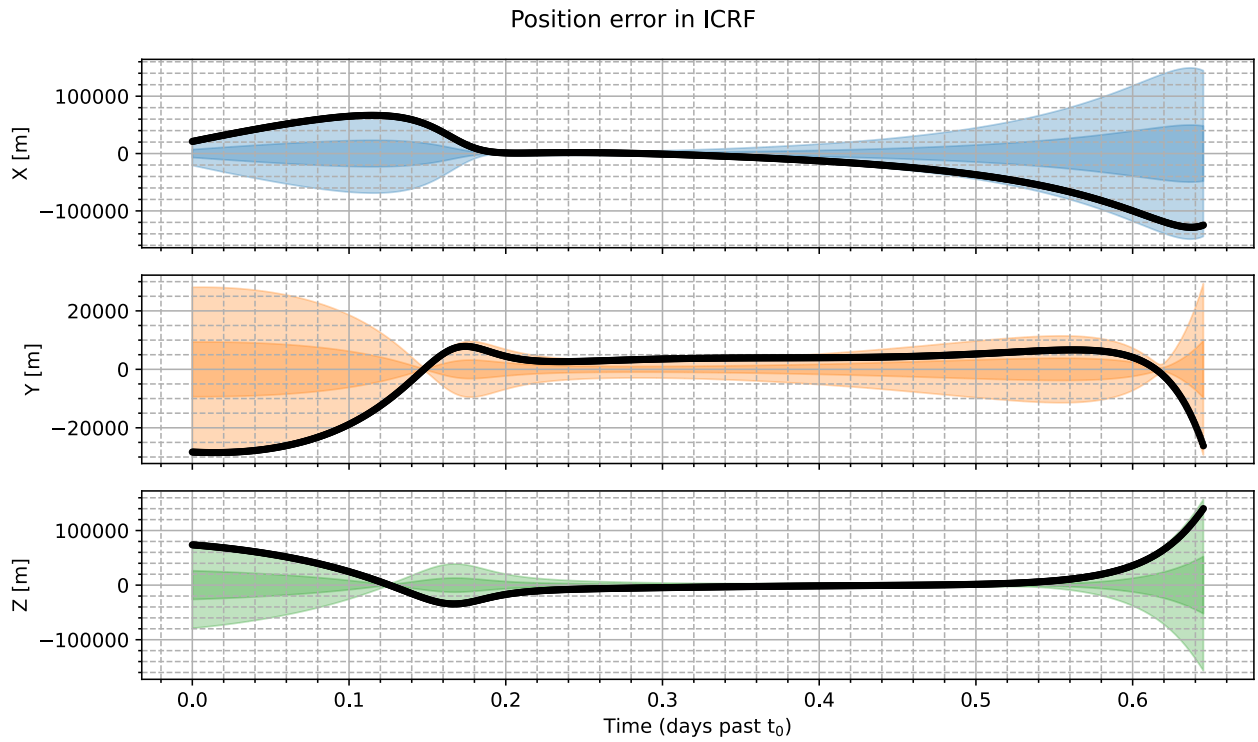


Figure 77. Position error of the OD with respect to the TLE 6 hours before and after the initial observation

The multi-site orbit determination was tested using data from two observatories, focusing on the Molniya object with NORAD ID 22671. Observations were carried out with AWARE and SCUDO, employing two contrasting strategies. AWARE captured 80 measurements across four 1-minute intervals, while SCUDO collected 700 measurements in a single 12-minute session. SCUDO's observations corresponded to the orbital pass immediately after the one monitored by AWARE. The aim was to evaluate whether the orbit determination based on AWARE's data was sufficient to initialize SCUDO's observations, which relied on TLE data to track the object. In Figure 78, Figure 79 and Figure 80 are shown the propagated data of the two passes and where in the trajectory the measurements were acquired for both the observatories.

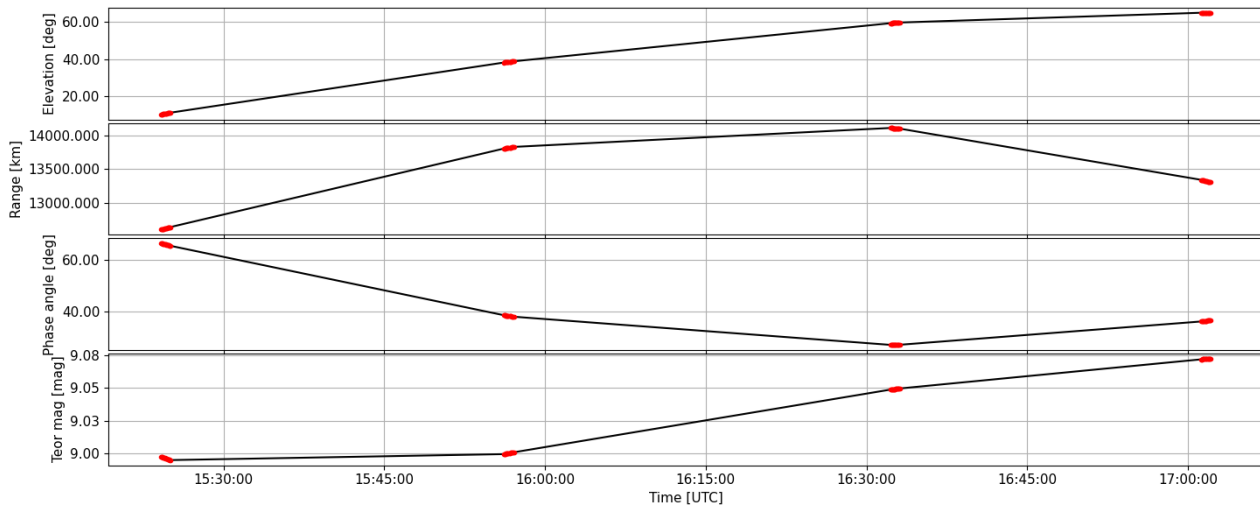


Figure 78. Propagated data and acquisition intervals for the AWARE observation

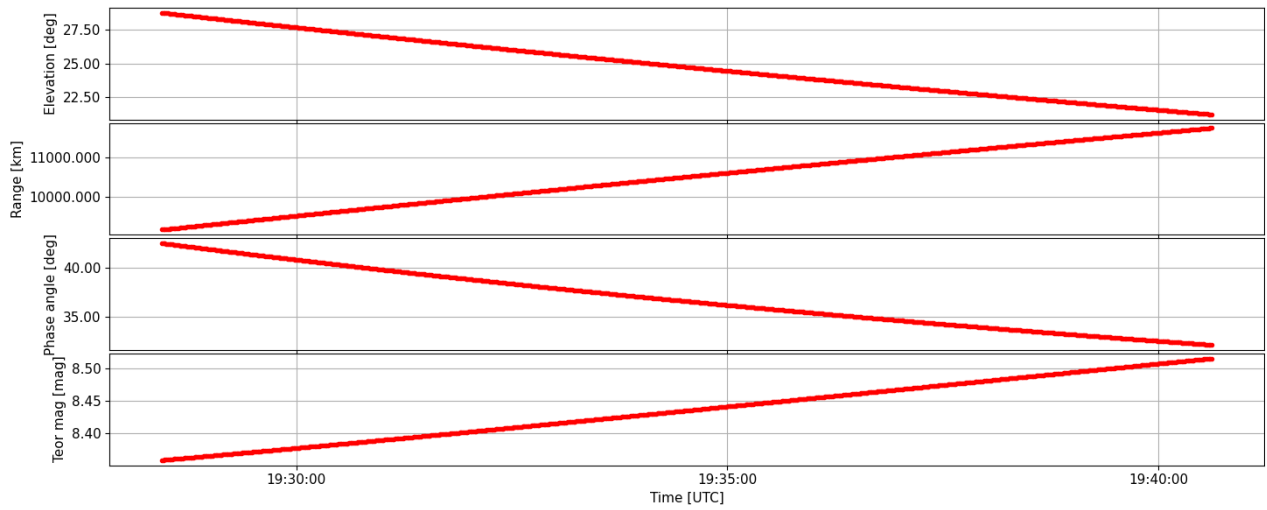


Figure 79. Propagated data and acquisition interval for the SCUDO observation

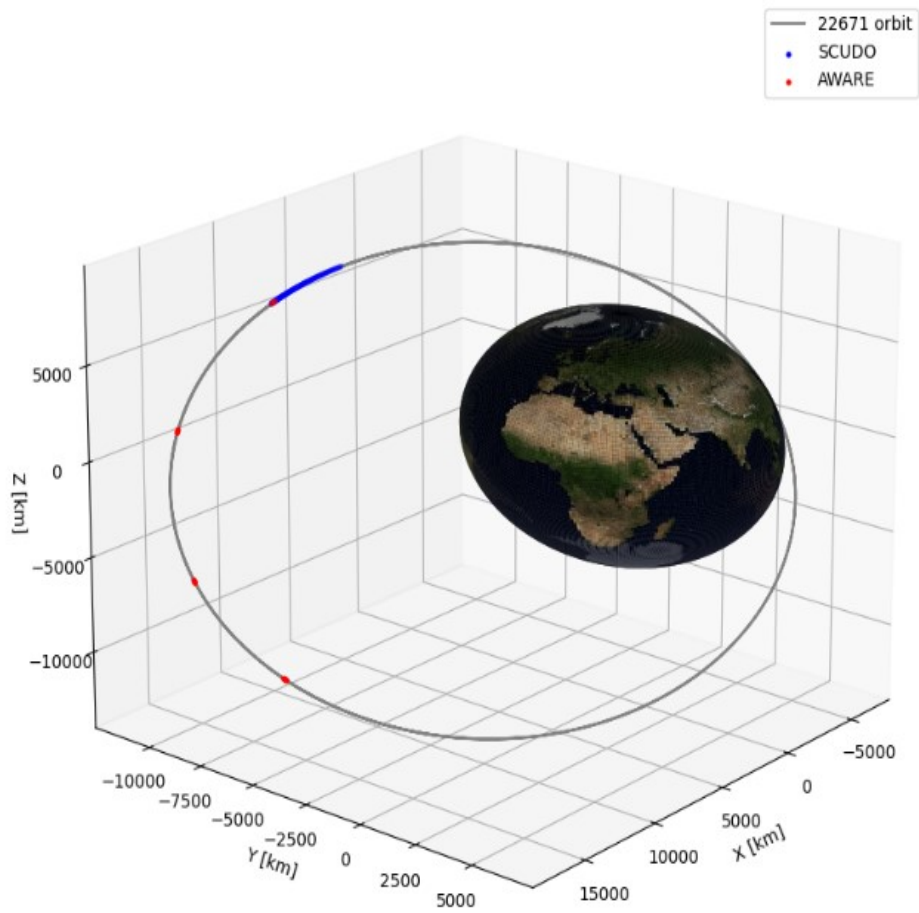


Figure 80. Target orbit and acquisition intervals for AWARE and SCUDO

In Figure 81, the differences in the RA/Dec plane are shown to evaluate whether the SCUDO observation could be initialized using the OD data from the AWARE observation. The differences between the OD results and the measurements acquired by SCUDO are smaller than those between the SCUDO measurements and the TLE, demonstrating that it is feasible to conduct observations using the RA and Dec obtained from the OD.

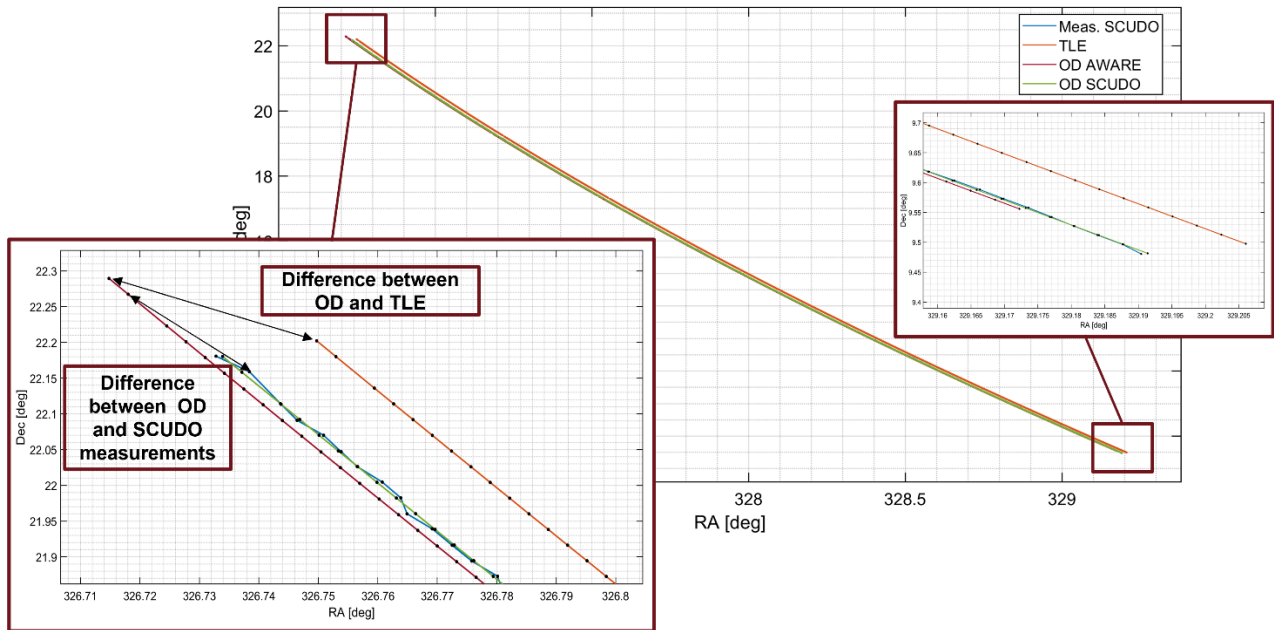


Figure 81. Difference between OD and TLE in the RA/Dec plane

In Figure 82 is also shown the difference in term of range between the OD and the TLE.

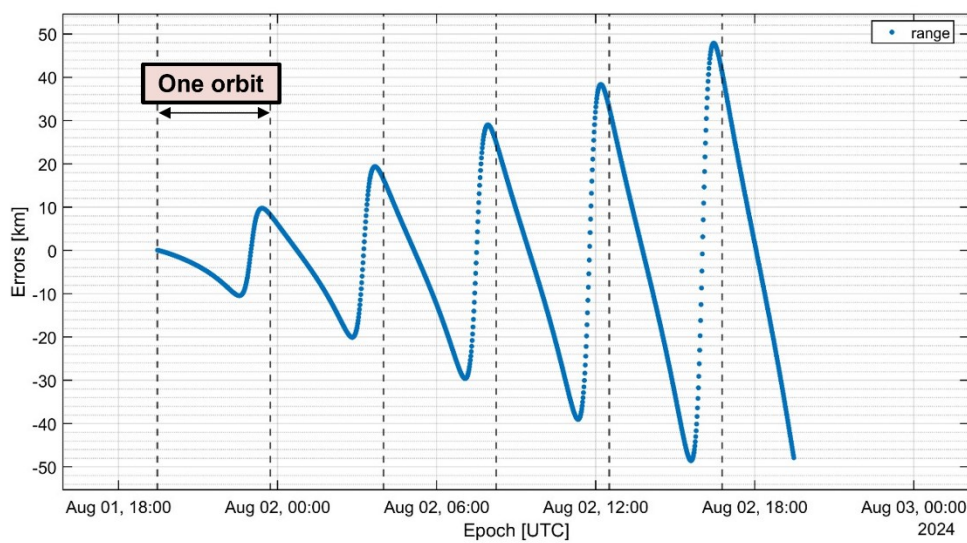


Figure 82. Error in range between OD and TLE in five orbits

In Table 12 are also shown the COE obtained with the different OD.

Table 12. COE comparison between TLE, OD performed using only AWARE data and then the OD with AWARE and SCUDO

COE	AWARE	OD with AWARE and then with SCUDO data	TLE
Semimajor axis [km]	13 343.652	13 339.662	13 340.371
Eccentricity	0.4898	0.4897	0.4895
Inclination [deg]	63.1490	63.1490	63.0128
RAAN [deg]	143.5987	143.5929	144.3598
Argument of perigee [deg]	19.9490	19.9261	19.7500
True anomaly [deg]	132.3114	157.1789	353.9938 (mean)

5.11.4. *Unknown objects case*

The analysis of unknown objects was conducted on the night of 2024-03-04, using the Mini-SURGE system. This system was chosen due to its wide field of view and its ability to capture images throughout the entire night in a fixed area of the sky. This makes it especially suitable for detecting uncatalogued objects, as the continuous observation over an extended period increases the likelihood of identifying objects that have not yet been catalogued. The data collected consisted of 400 total frames, resulting in 8057 catalogued measurements and 742 non-catalogued measurements. All the acquired measures of Mini-SURGE during the night of 2024-03-04 are shown in black in Figure 83.

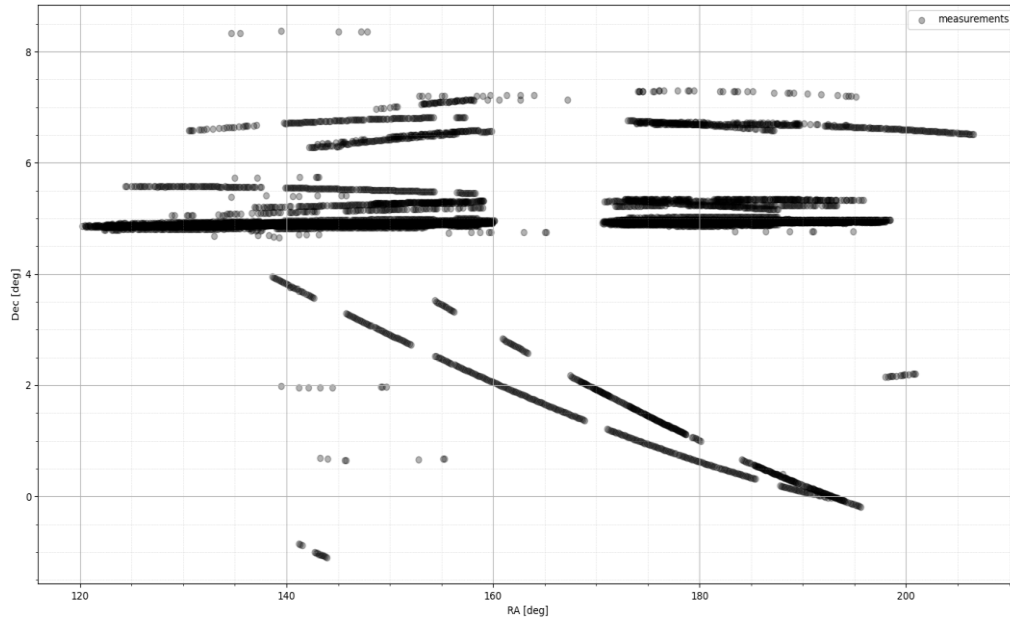


Figure 83. All the acquired measures of Mini-SURGE during the night of 2024-03-04

Table 13 further highlights that 2 objects were visible but undetected, while 5 catalogued objects were not visible at all.

Table 13. Breakdown of the expected objects in the field of view, detected objects, and the categorization of measurements

Expected objects in FoV from propagation	55
Detected expected objects	48 (87%)
Visible undetected objects	2 (4%)
Not visible objects	5 (9%)
Total acquired frames	400
Total catalogued measurements	8057
Total non-catalogued measurements	742
Unknown objects	14
Total detections (catalogued + unknown)	60

During this observation, a total of 60 objects were detected, 14 of which were classified as unknown as shown in Figure 84.

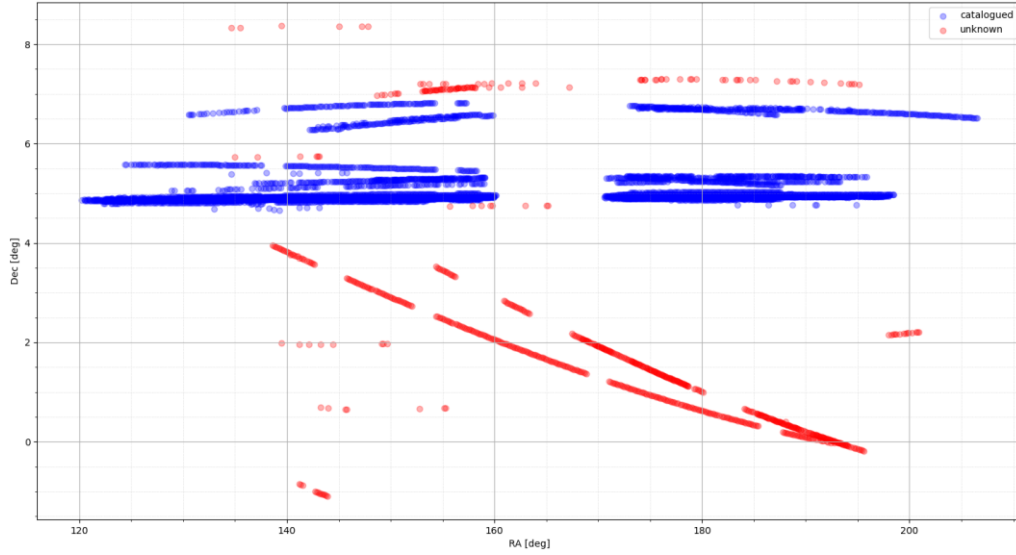


Figure 84. Measures of catalogued objects (blue) and not catalogued one (red)

The process of measurements association involves linking multiple sets of observations to the same object. The procedure begins by selecting an initial tracklet of measurements and performing orbit determination based on this data. The resulting orbital state is then propagated to the times corresponding to the other tracklets. To identify potential matches, the propagated positions are compared with the observed measurements, applying specific criteria such as differences in right ascension, declination, and line-of-sight. If a match is found that satisfies these conditions, the two tracklets are associated, and the process is repeated by updating the orbital state using the combined data. This iterative approach ensures that the orbit determination benefits from progressively more data, improving accuracy and reducing uncertainties in the object's trajectory. The associated objects are shown in Figure 85 where are displayed only the unknown objects.

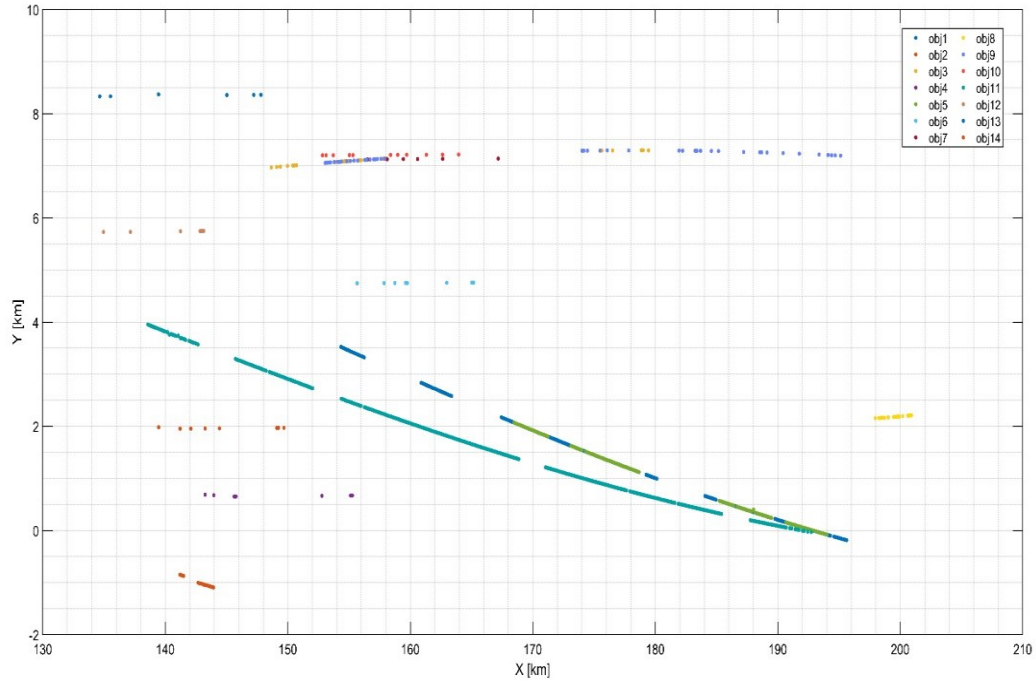


Figure 85. Measurements divided by object with the association procedure

Once the measurements are separated by object, OD is performed for each identified object. Figure 86 displays the orbits of the identified objects, providing a clear representation of their trajectories based on their orbital parameters.

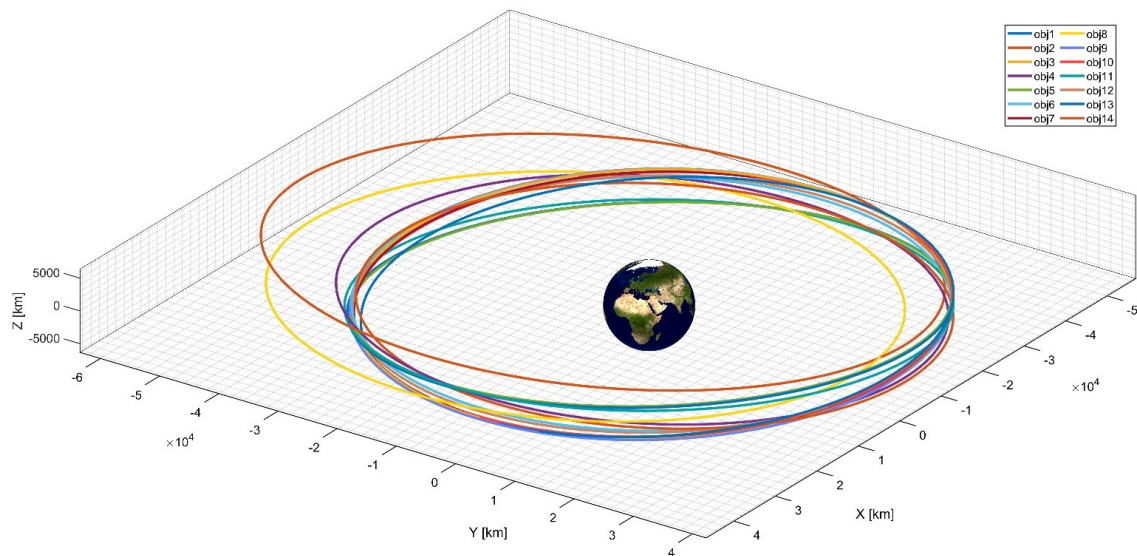


Figure 86. Trajectories of unknown objects for both cameras of Mini-SURGE (2024-03-04)

In Figure 87 the differences in orbital parameters between catalogued and unknown objects are shown.

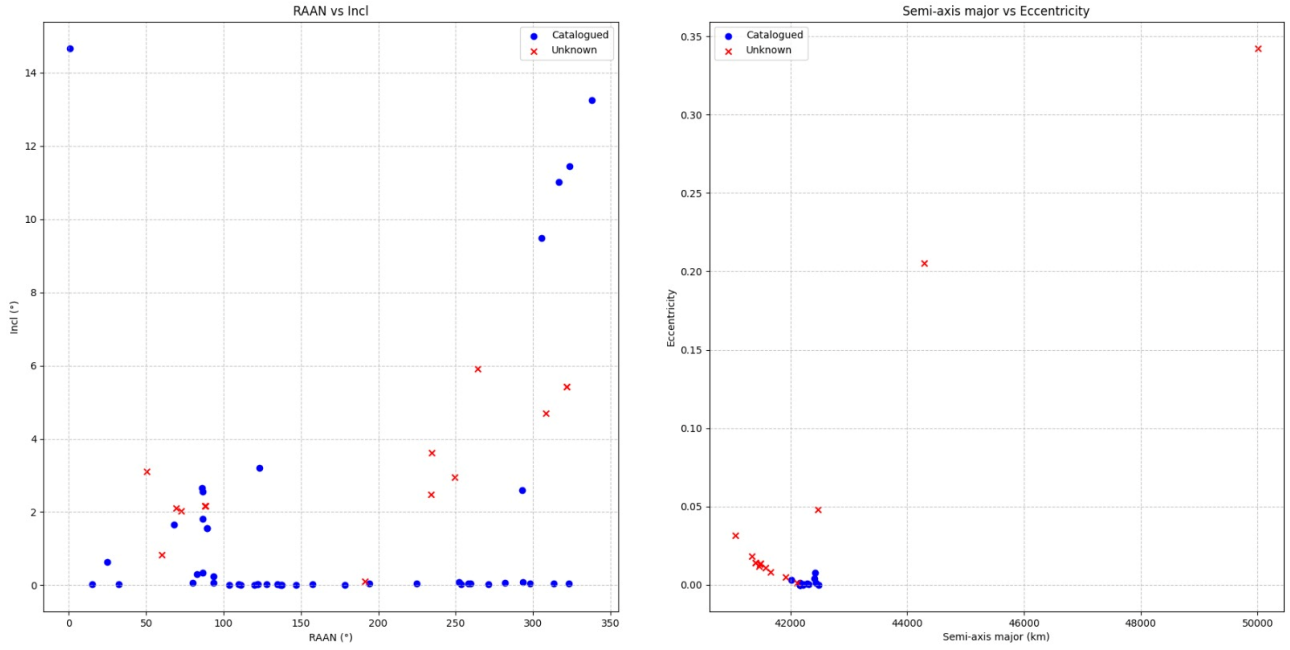


Figure 87. RAAN versus Inclination (left) and Semi-axis major versus Eccentricity (right) for the catalogued (blue) and for unknown (red) objects detected with Mini-SURGE

In the RAAN versus inclination plot, the catalogued objects form a tight cluster at low inclinations (below 2 deg), consistent with geostationary orbits, which are nearly equatorial to maintain a fixed position relative to the Earth's surface. In contrast, the unknown objects display a broader spread in inclination, reaching up to 8 deg. This distribution reflects geosynchronous orbits, which can have higher inclinations while maintaining a 24-hour orbital period, resulting in more varied orbital paths. In the semi-major axis versus eccentricity plot, the catalogued objects are concentrated near a semi-major axis of approximately 42000 km with near-zero eccentricities, typical of geostationary orbits that are circular and maintain constant altitude. The unknown objects, however, show a significantly wider range of eccentricities, reaching up to 0.35, along with slight variations in their semi-major axes. These features are characteristic of geosynchronous orbits, which can be more elliptical. Overall, the graph highlights a distinct separation between the catalogued and the unknown objects, especially in the semi-major axis versus eccentricity plot.

6. Object detection with neural networks

At the end of 2023, after several tests of different neural networks such as U-NET, the YOLO network was developed to identify all satellites within the field of view. Integrating the neural network into FATE took a considerable amount of time as the training strategy had to be understood, datasets had to be created for training the cameras, and various training attempts had to be made. Furthermore, it was necessary to modify the neural network code to accept images in FITS format, since the YOLO network was originally designed for processing 8-bit RGB images, while the images from the observatories cameras are 16-bit grayscale. As the network identifies all objects within the field of view, it was also necessary to implement an association strategy to ensure that information is extracted from the correct object in the field of view.

The main inputs to the routine are the timestamped raw frames (in FITS format) produced by each camera. Those frames are pre-processed with standard calibration and then the stellar field resolution is performed. The output of the last activity is World Coordinate System (WCS) file, that allows the conversion between pixel and celestial (i.e. RA/Dec) coordinates. The single frame analysis activity converts the single frame to a set of single line timestamped coordinates, i.e., a TDM line relative to a single frame. At the end of the last data processing thread each single line is merged into a compiled TDM-file. The software runs a Machine Learning (ML) based object detection algorithm that allows it to identify and track objects in the frames by generating bounding boxes around them. The central coordinates of the boxes are used to calculate the precise object centroids used for flux calculations. In a parallel activity the WCS file is used for the pixel coordinate conversion for each object. The data activity diagram is shown in Figure 88.

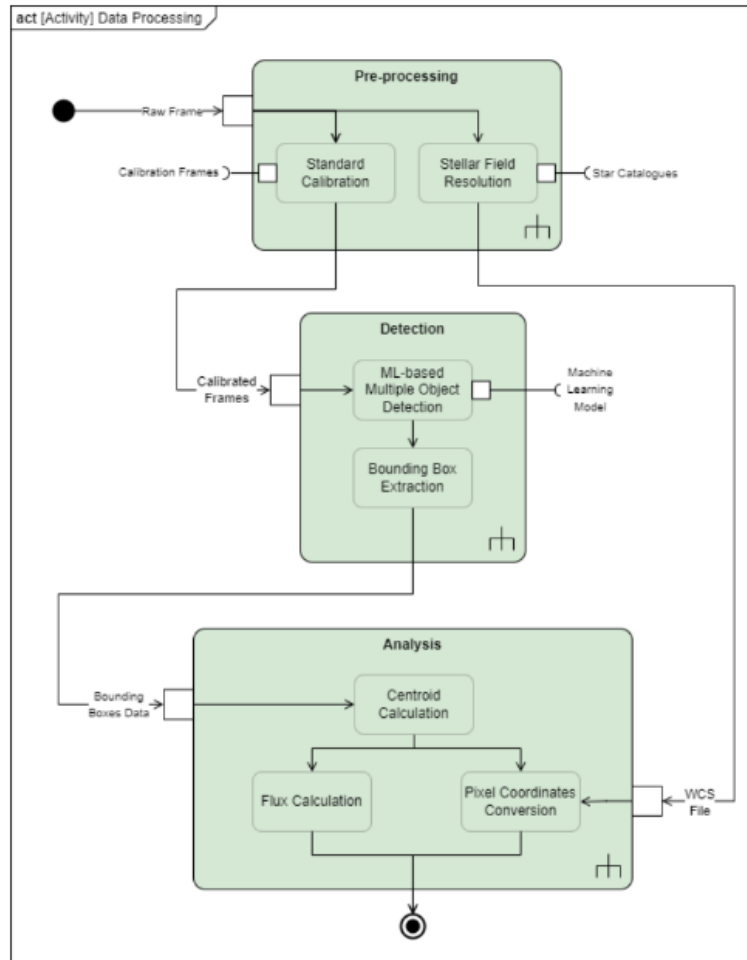


Figure 88. Data processing diagram

6.1. Introduction to neural networks

The first applications of CNNs in astronomical object recognition primarily focused on the identification and classification of stars and galaxies in large sky surveys, yielding promising results in terms of accuracy and processing speed. In the specific context of satellite recognition, however, the application of CNNs is still an emerging field, with various approaches proposed to address the unique challenges associated with analyzing moving artificial objects. One of the main advantages of CNNs in this area is their ability to automate the satellite detection process, even in images with high noise levels or highly variable brightness, leveraging the CNNs' ability to adapt to different acquisition conditions. Recent studies have employed CNNs to detect artificial objects in orbit using customized

architectures or pre-trained models adapted to the peculiarities of astronomical observations. For example, networks like ResNet and YOLO have been modified to optimize satellite detection, yielding encouraging results in identifying faint objects and in low-contrast conditions typical of astronomical images. Other approaches make use of data augmentation techniques to increase the diversity of training data, thereby enhancing the CNNs' ability to generalize to new scenarios and to recognize objects that differ in shape and brightness from natural celestial objects. Despite the progress, the use of CNNs for the automated monitoring and classification of satellites in SSA/SST is still limited by several factors. One of the main obstacles is the limited availability of high-quality labelled datasets, which are essential for training the networks. Furthermore, the variability in satellite orbits and light signatures requires models that are both highly accurate and robust to differences in brightness and position within the field of view.

6.2. Advantages and challenges

The CNNs advanced capabilities in image processing and pattern recognition enable high accuracy and rapid analysis, addressing key challenges in the SSA domain. By efficiently processing vast amounts of image data in real time, CNNs facilitate the detection and classification of various objects, crucial for maintaining a comprehensive understanding of orbital environments. One of the primary advantages of CNNs lies in their scalability, which makes them well-suited to handling the data from diverse observation sources. Their robustness to noise, a prevalent issue in astronomical imaging, further enhances their utility by filtering irrelevant information and ensuring that critical details remain intact. This adaptability extends to varying distortions and environmental conditions, ensuring reliable performance under diverse operational scenarios. Automation is another critical benefit offered by CNNs, significantly reducing the need for continuous human intervention. This capability is especially advantageous for 24/7 monitoring operations, where CNNs can process and analyze images in real time.

Despite these advantages, several challenges must be addressed. A primary concern is the need for extensive, high-quality training datasets. The creation of labelled datasets that encompass the diversity of objects and conditions encountered in space is resource-intensive and costly. Additionally, the computational demands of training and deploying CNNs, especially for real-time applications, necessitate advanced hardware, such as GPUs, which can lead to higher operational costs. Overfitting is another concern, where a model performs well on training data but struggles with new, unseen data. This risk is particularly significant in the space environment, where new objects and conditions frequently emerge. Mitigating this requires continuous updates and retraining of models with new datasets, a logistically complex and ongoing process. Furthermore, CNNs' inherent complexity and "black-box" nature make their decision-making processes difficult to interpret, posing challenges for validation and optimization. The variability of the space environment, including differing lighting conditions, perspectives, and object distances, presents further difficulties for CNNs. These factors affect image quality and algorithm performance, emphasizing the need for high-quality sensor data. Poor resolution or noise-laden images can severely impact CNN accuracy, highlighting the importance of robust pre-processing and sensor calibration. Hereafter, a synthetic list of challenges and benefits in using the CNN are reported:

Challenges:

- **High-Quality Dataset Requirements:** Effective training requires large, labelled datasets that are representative of the operational conditions. Insufficient data can lead to overfitting, limiting generalization.
- **Complexity and Interpretability:** The "black box" nature of CNNs makes their internal operations opaque, complicating decision validation and optimization.
- **Computational Resources:** Training and deployment often require substantial computational resources, particularly for high-resolution data.

- **Environmental Variability:** Diverse operational conditions, such as noise and low resolution, can affect performance, necessitating robust models and pre-processing techniques.
- **Maintenance:** Continuous updates and retraining are necessary to maintain model performance as new data becomes available.

Benefits:

- **Efficiency:** CNNs can be optimized to run on accessible hardware, such as low-cost GPUs, reducing operational costs.
- **Automation:** Pre-processing steps, such as noise reduction and background star filtering, can be automated, minimizing manual intervention.
- **Speed:** CNNs enable real-time detection and processing of large data volumes, essential for continuous sky monitoring.
- **Multi-Scale and Multi-Object Detection:** CNNs can simultaneously detect objects of varying scales and multiple objects in a single image, enhancing operational efficiency.
- **Continuous Improvement:** CNNs improve over time with additional data, becoming more accurate and reliable.

In summary, while CNNs offer significant advantages in satellite detection and analysis, their application requires addressing challenges related to data acquisition, computational demands, and environmental variability. With proper development and optimization, CNNs can play a pivotal role in advancing autonomous SSA capabilities, enabling more efficient and reliable monitoring of the orbital environment.

6.3. YOLO and YOLO v5 object detection

YOLO stands for “You Only Look Once”. Its name refers to its fast detection process, thanks to its operation. While algorithms like Faster RCNN work by detecting possible regions of interest using the Region Proposal Network and then performing recognition on those regions separately, YOLO performs all of its predictions with the help of a single fully connected layer, therefore the image is only passed once through a CNN. Several new versions of the same model have been proposed since the initial release of YOLO in 2015, each building on and improving its predecessor [31]. Compared to other object detection systems, YOLO was extremely fast since its very first versions. Moreover, it sees the whole image during training and testing, then implicitly encodes contextual information about classes and their appearance. In the end, it learns generalizable representations of objects so that when trained on natural images and tested on works of art, the algorithm outperforms other high-level detection methods. The network is structured in three main components:

- the backbone, which is a convolutional neural network that aggregates and forms image features at different granularities;
- the neck, which is a series of layers to mix and combine image features to pass them forward to prediction;
- the head, which is composed of consumers’ features from the neck, and it takes the box and class prediction steps.

The base architecture of YOLO is shown in Figure 89.

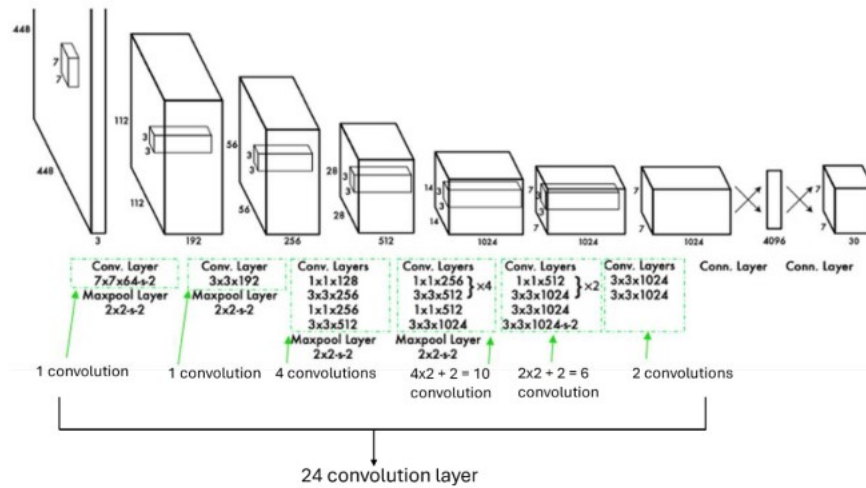


Figure 89. YOLO architecture [32]

YOLO v5 was introduced in 2020 by the same team that developed the original YOLO algorithm as an open-source project and is maintained by Ultralytics. YOLO v5 builds upon the success of previous versions and adds several new features and improvements. Unlike YOLO, YOLO v5 uses a more complex architecture (Figure 90) called EfficientDet, based on the EfficientNet network architecture [33].

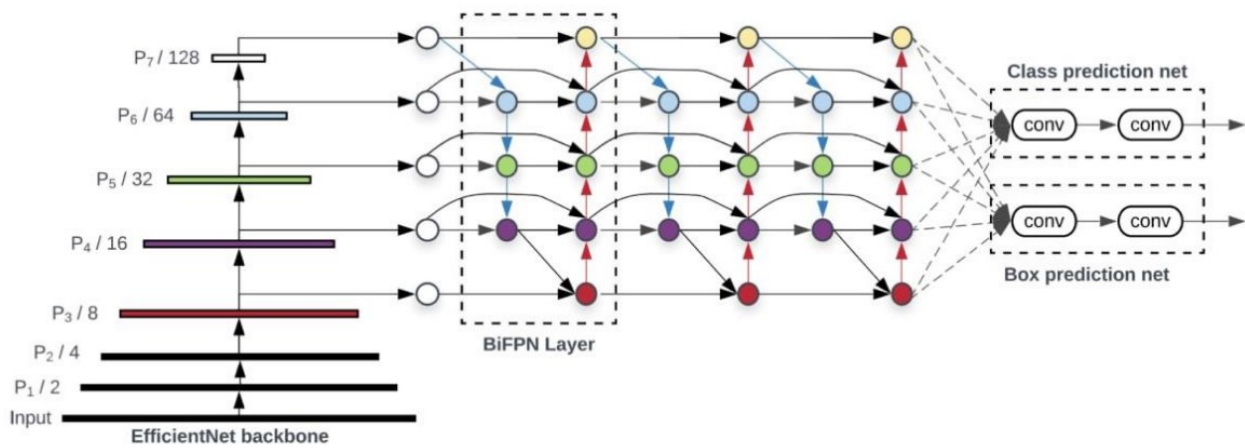


Figure 90. YOLO v5 architecture [33]

Using a more complex architecture in YOLO v5 allows it to achieve higher accuracy and better generalization to a wider range of object categories. Moreover, YOLO was trained on the PASCAL VOC dataset, which consists of 20 object categories. YOLO v5, on the other

hand, was trained on a larger and more diverse dataset called D5, which includes a total of 600 object categories. YOLO v5 uses a new method for generating the anchor boxes, called "dynamic anchor boxes." It involves using a clustering algorithm to group the ground truth bounding boxes into clusters and then using the centroids of the clusters as the anchor boxes. This allows the anchor boxes to be more closely aligned with the detected objects' size and shape.

6.4. Training

The fifth version of YOLO has been implemented in FATE for its One-Shot approach that consists in applying a single convolutional neural network directly to the image to perform object detection and classification simultaneously, resulting in very fast running times [32]. The objective is to detect all the objects in the image, associate every object with its class and provide the coordinates of the bounding boxes that delimits it. The model was trained with a dataset derived from a selected set of images obtained from the observatories. The speed of the neural network is of great help in processing the big amount of data acquired from the system.

To face the complications related to the memory used during the training of the AI model, the processing of each small ROI composing the full image is performed separately. In this way, the amount of data to process meets the technical potential of the machine. To train a valid AI model, the training inputs must be as similar as possible to the inputs that will be processed by it. During the dataset's building, therefore, the same steps followed during the image analysis are performed. The steps are summarised by the flowchart in Figure 91 and they are described below.

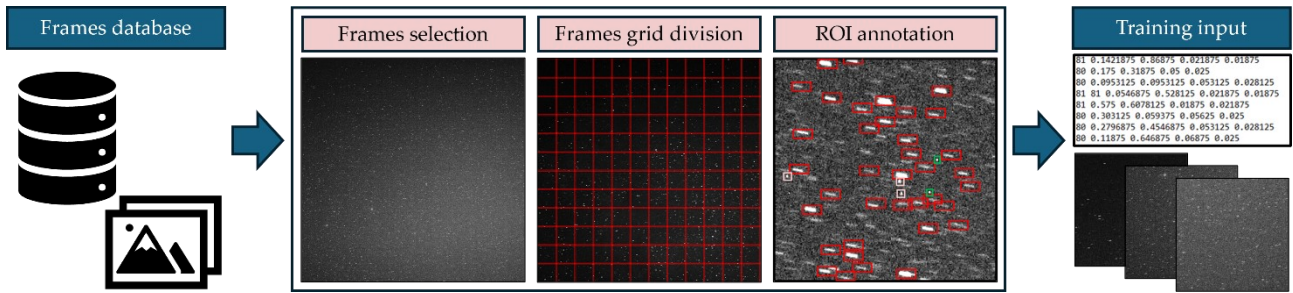


Figure 91. Dataset's building flowchart

The initial step in developing a robust dataset is the careful selection of frames that represent a wide range of scenarios. For instance, a dataset comprising 1000 images in .png format, each with a resolution of 320x320 pixels, would typically occupy approximately 300 MB of storage space. The time required to process and organize such a dataset depends on factors such as the number of sources inside the images. For example, extracting, labelling, and formatting 1000 images might take several hours, or days, if done manually. Each image must be divided into smaller ROIs that can be processed by the neural network overcoming the memory-related problems encountered by the full image. For this step, a grid is created on the image which is later cut into multiple ROIs. To avoid losing information on the boundaries that divide each ROI from the others, an overlap of a few pixels is considered. The number of pixels used for the overlap for each edge of the ROI is chosen as the quantity of pixels that a GEO object occupies in the system's images on average, which is around 8, plus a tolerance factor of 8 pixels. ROIs derived from cropping the images are one of the two constituents of the dataset for the neural network's training. The second input is composed of label files, each of which corresponds to its ROI image. Lines of the file correspond to the labelled objects, while each column is filled with a different parameter that describes them. First column specifies the class to which the object belongs. The model is specifically trained to differentiate between stars and objects. Second and third columns contain respectively the abscissa and ordinate values of the centre of the BB built around the object, while fourth and fifth columns contain width and height of the BB. An external software is used in this step to create the label files. The program allows the user to interact with the ROIs by visualising them and drawing the desired bounding box around the objects. Images and

corresponding label files are given as inputs for the model's training. During training, a customizable percentage of the dataset is set aside for model validation and is not included in the actual training process. This percentage is set to 20% for the model presented in this thesis. The training is therefore performed on 80% of the data. At the end of the training the model is validated on the rest of the data by the comparison between the predictions of the model on the images and the label files from the validation dataset.

An example of the validation's output is shown in Figure 92. On the right, the bounding boxes of the model's predictions are shown together with the associated probability scores. The validation is carried out through the comparison with the bounding boxes given as input to the training, shown on the left.

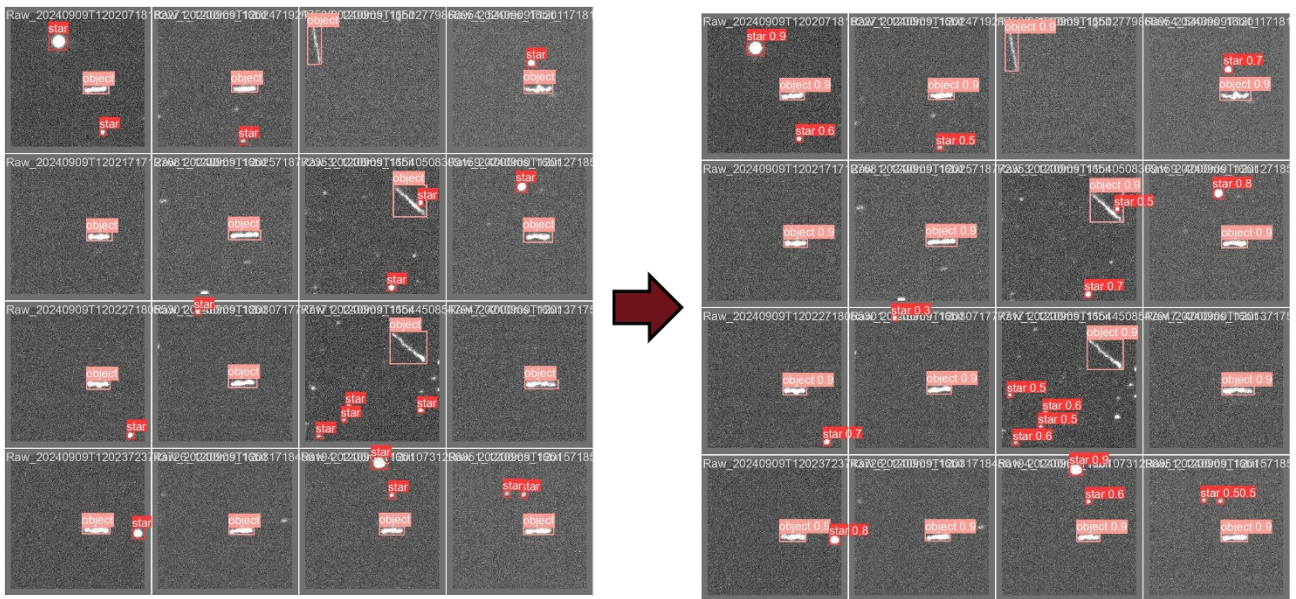


Figure 92. Example of validation output given by YOLO. On the left the input label, while on the right the detected ones with related probability

In training object detection models such as YOLO, evaluation metrics are crucial for assessing model performance and accuracy in detecting and classifying objects. Key metrics include precision, recall, and mean Average Precision (m_{AP}), with specific thresholds such as m_{AP} 50 and m_{AP} 50-95 that determine detection quality based on Intersection over Union (IoU) thresholds.

$$IoU = \frac{\text{Intersection area}}{\text{Union area}} \quad (30)$$

Precision measures the proportion of correctly detected objects out of all predicted detections, giving insight into the model's ability to avoid false positives (FP). It is defined as:

$$\text{precision} = \frac{TP}{TP + FP} \quad (31)$$

Where TP are the true positive and FP the false positive. Recall quantifies the model's ability to detect all relevant objects, thus reflecting the model's sensitivity to true objects in the dataset. It is calculated as:

$$\text{recall} = \frac{TP}{TP + FN} \quad (32)$$

Where FN are the false negative. High precision indicates that the model accurately classifies detected objects, while high recall signifies that the model detects most of the true objects in the images. $m_{AP} 50$ and $m_{AP} 50-95$ are variations of mean Average Precision (m_{AP}), which provides a comprehensive evaluation of the model's performance across multiple IoU thresholds. For each class, Average Precision (AP) is calculated by measuring the area under the precision-recall curve. Then, m_{AP} is the average of AP across all classes:

$$m_{AP} = \frac{1}{N} \sum_{i=1}^N AP_i \quad (33)$$

where N is the number of object classes. In particular, $m_{AP} 50$ calculates AP at a single IoU threshold of 0.5, meaning the predicted bounding box must have at least 50% overlap with the ground truth box to be considered a true positive. $m_{AP} 50-95$ is a more stringent metric that averages AP across multiple IoU thresholds, from 0.5 to 0.95 in 0.05 increments. This metric, provides a more detailed assessment of model accuracy, rewarding models that can make precise detections at various overlap levels.

The YOLO network was trained for sidereal tracking using images collected from multiple observatories, as depicted in Figure 93, which shows a pie chart of the percentage distribution of images used in training. Utilizing data from various observatories enhances the model's generalization, making it effective across different observational environments.

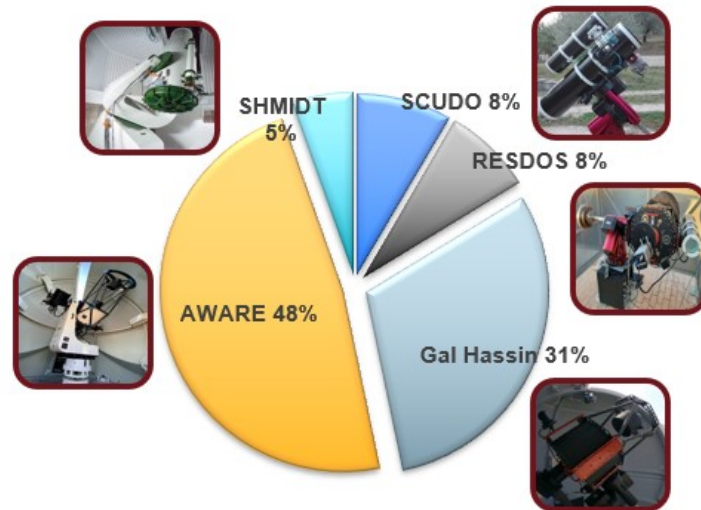


Figure 93. Dataset pie chart with images percentage from different observatories

Additionally, these images were produced with diverse optical configurations and sensor types, further broadening the model's adaptability to varying equipment setups. The dataset also includes a range of lighting conditions, which helps the model perform reliably under diverse illumination scenarios. Table 14 summarizes the performance metrics of a model evaluated on a dataset containing 871 regions of interest (ROI) and 1,635 labelled instances across two classes, Star and Object. The metrics include Precision, Recall, mAP50, and mAP50-95.

Table 14. Metrics for the sidereal tracking trained model

Class	ROI	Label	Precision	Recall	mAP50	mAP50-95
All	871	1635	0.812	0.911	0.853	0.612
Star	871	768	0.628	0.792	0.712	0.386
Object	871	867	0.972	1.000	0.994	0.838

For the combined dataset (All classes), the model achieves a precision of 0.812, indicating that 81.2% of the detected instances are correct. The recall of 0.911 demonstrates that 91.1% of the actual instances in the dataset were successfully detected. The mean Average Precision at 50% Intersection over Union (mAP50) reaches 0.853, reflecting the model's overall ability to balance precision and recall, while the mAP50-95 is 0.612. Breaking down the results by class, the Star class exhibits a precision of 0.628 and a recall of 0.792, resulting in an mAP50 of 0.712 and an mAP50-95 of 0.386. This suggests that while the model is reasonably effective at identifying stars, there is room for improvement, particularly in precision and under stricter evaluation criteria. The Object class, on the other hand, demonstrates high performance, with a precision of 0.972 and a perfect recall of 1.000, meaning all objects were accurately identified. The mAP50 for this class is a remarkable 0.994, and the mAP50-95 is 0.838, indicating robust performance even under stringent evaluation conditions. These results highlight the model's strength in detecting Objects while revealing challenges in achieving similar performance for the Star class. Further optimization, particularly in refining the model's capability to distinguish Stars more precisely, could enhance overall effectiveness.

Deterministic algorithms, such as ASTRIDE or SExtractor, often struggle when an object's shape is distorted by noise or other factors, leading to incomplete or inaccurate detection. To evaluate the reliability of the trained neural network, a comparison test was conducted against ASTRIDE algorithm. The test involved analyzing a set of 78 frames captured during the sidereal tracking of a geostationary object, specifically the Beidou satellite with catalog number 41586. This dataset presented challenges typical of real observations, such as noise and distortions, providing a robust basis for assessing the performance of both methods in detecting and characterizing the object. In Table 15 is reported the result of the test.

Table 15. Comparison between the trained YOLO model and the ASTRIDE algorithm

	ASTRIDE	YOLO v5
Objects	44 / 78 (56%)	78 / 78 (100%)

Missing detections	34 / 78 (44%)	0 / 78 (0%)
False detections	46	0
Mean time	4.2 s / frame	1.1 s / frame
Total time	331 s	87 s

The comparison between ASTRIDE and YOLO v5 highlights notable differences in detection performance and processing efficiency. YOLO v5 successfully detected objects in all 78 frames (100%), while ASTRIDE detected only 56% of the objects, missing 44% of the targets. Additionally, YOLO v5 produced no false detections, whereas ASTRIDE introduced 46 false positives, indicating a higher susceptibility to errors. In terms of computational performance, YOLO v5 demonstrated a significant advantage, with an average processing time of 1.1 seconds per frame compared to ASTRIDE's 4.2 seconds, resulting in a total execution time that was nearly four times faster.

6.5. Measurements association

The measurement association process is a step in the pipeline, aimed at correctly assigning measurements to the same object across a sequence of frames. In FATE, this task is performed using a k-means clustering algorithm, specifically tailored for TLE tracking. The entire process is shown in Figure 94.

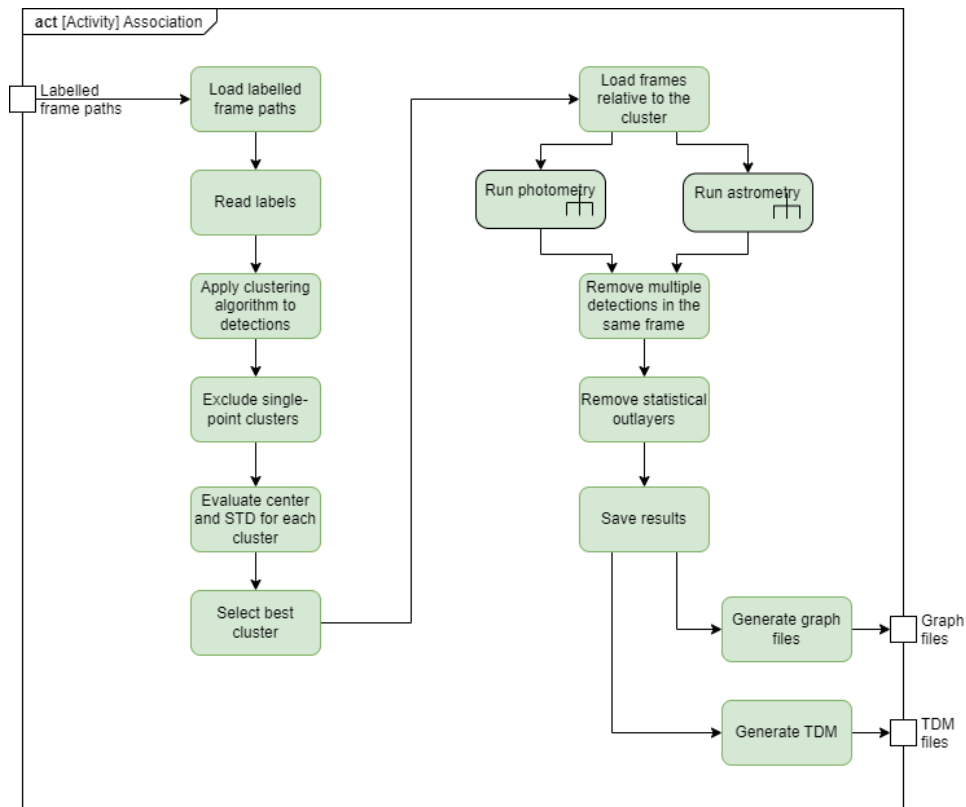


Figure 94. Association activity diagram

The method involves analysing all acquired frames and plotting the x,y coordinates of detected objects in the image plane. The analysed frames are divided into small ROIs with the same procedure followed for the training dataset. The AI model makes instances on each ROI, specifying coordinates and dimensions of the BBs that delimit the detected objects, the classes to which they belong, and the scores assigned to the predictions. The output of the prediction, given in the ROI's reference frame, is then converted into the full image's reference frame. In this way, the objects' coordinates represent their positions in the original image, and they can be plotted on it. In TLE tracking, the observed object is typically unique, and it is expected to remain near the center of the FoV. Additionally, if the TLE used is sufficiently recent and has no significant errors, the tracked object will appear relatively stationary throughout the acquisition sequence.

An illustrative example of this process is shown in Figure 95, which depicts an observation of a geostationary satellite cluster. In this case, the tracked object, corresponding to the primary satellite of interest, is located near the center of the FoV. However, other objects, both

geostationary and geosynchronous, are also visible. These objects appear in positions different from the tracked satellite and exhibit a slight drift during the sequence due to their relative motion with respect to the observer.

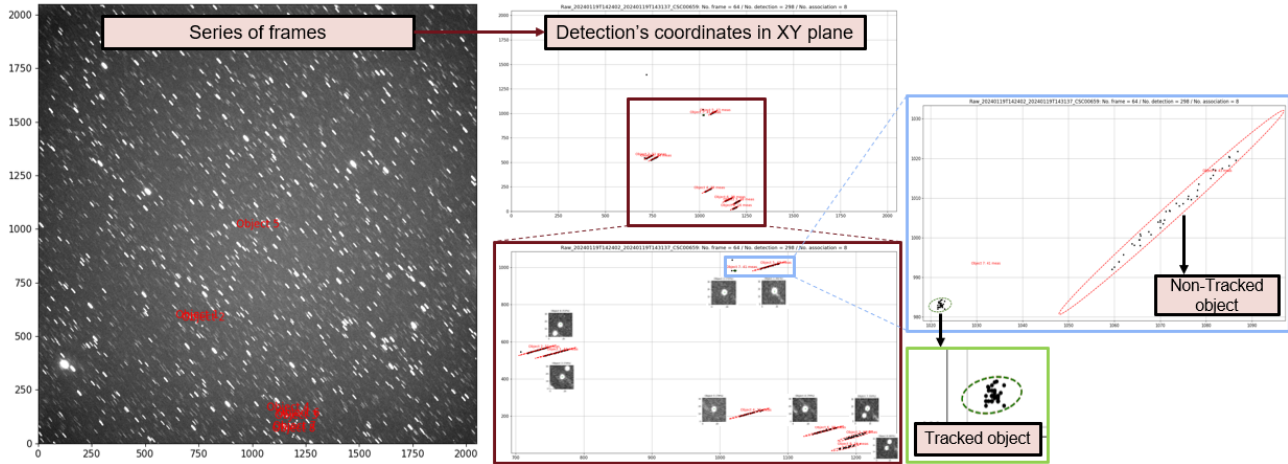


Figure 95. Measures in terms of x,y of all the detected objects. An highlight of the cluster of the tracked object (green) and of a non-tracked object (red)

As the figure shows, both the tracked and non-tracked objects are detected, because AI detection preserves from the knowledge of orbital parameters. The tracked object is represented by the cluster with the lowest standard deviation, eccentricity and distance to the center.

In Mini-SURGE, the measurement association process is implemented with some key differences, tailored to its fixed-pointing operational mode. Since the system observes the same portion of the sky continuously, the clusters with minimal drift or very narrow dispersion in terms of point distribution (and thus lower standard deviation) correspond to geostationary satellites. Conversely, clusters that exhibit more significant drift over time are associated with geosynchronous satellites, which have relative motion within the observed FoV. An example of this distinction is provided in Figure 96, where two zoomed-in views of clusters identified within the same image are displayed. These examples highlight the difference in cluster characteristics: the geostationary satellite clusters are compact and stationary, while the geosynchronous satellite clusters show greater spread and movement. The zoomed-in views were included because the original image spans more than 5000 pixels, making it

challenging to visually discern the clusters and appreciate their distinct shapes and distributions.

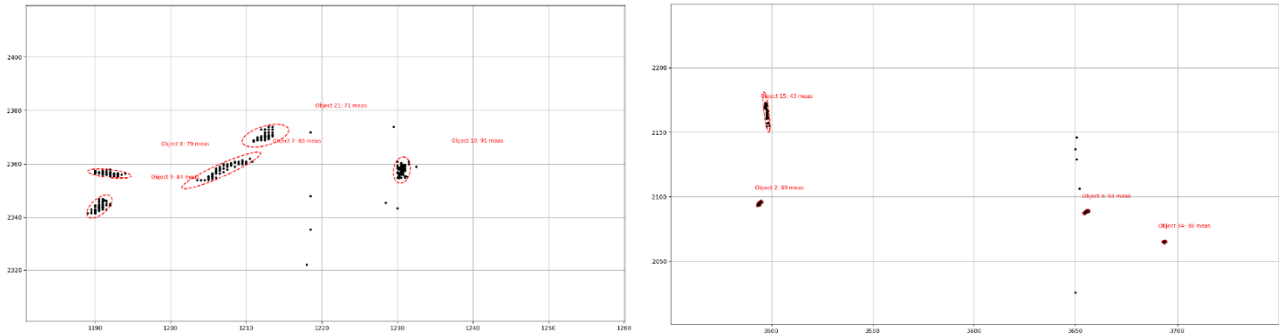


Figure 96. Enlarged views of two distinct regions of clusters identified within the same image captured by the miniSURGE system.

This clustering process also serves in excluding measurements that do not correspond to an object, filtering out false detections. By grouping all measurements into clusters, the algorithm can identify and discard those that do not exhibit the expected motion patterns. For instance, detections corresponding to stars, which might initially appear similar to objects due to brightness or shape, can be differentiated and excluded based on their non-static positions in the image sequence. Similarly, false positives resulting from sensor noise or image artifacts are identified as outliers, as they typically fail to form coherent clusters. This automated filtering significantly improves the reliability of the object association process, ensuring that only valid measurements are retained for further analysis.

7. Validation and qualification campaigns

7.1. AWARE validation and qualification

Currently, the centroid calculation as proved as effective on a typical observation night, and has been implemented to analyze images from the cameras in real-time. However, object identification quality can decrease due to various reasons, including the presence of clouds in the frames or strong wind during acquisitions. Additionally, the analysis of some very bright LEO satellites can produce worse results due to the training being conducted

primarily with data from GEO satellites. In conclusion, the network training can be improved by adding a greater number of satellites to the training data, especially bright LEO satellites. It is not possible to determine whether the analysis fails due to atmospheric factors since the station does not have that data and therefore FATE cannot know. Therefore, for the such verification, it is necessary to visually verify the cause of the analysis failure. In Figure 97 are reported the main information about the acquired data with the AWARE station from the 2024-06-01 to the 2024-11-01.

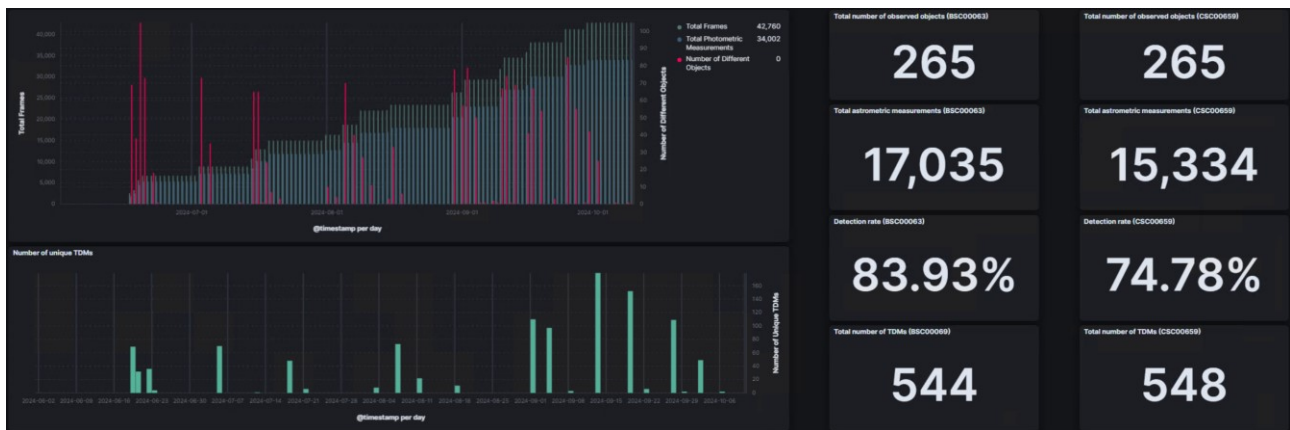


Figure 97. Data acquired with the AWARE station in 5 months of observation

In 5 months of observations 265 objects were observed with around 30000 total number of measurements stored in around 1000 TDMs. The detection rate, that is calculated dividing the number of measurements over the number of frames without considering multiple detection in one frame, show an average of about 85% for the primary camera and 75% for the secondary camera.

In collaboration with the ESA Expert Centre, an observational campaign was conducted to evaluate the operational performance of the telescope against key performance indicators (KPIs). The results, outlined in Table 16, compare the observed sensor performance with baseline requirements.

Table 16. ESA Expert Centre table of KPIs and results obtained during the validation campaign

KPI	Baseline requirement	Observed performance of the sensor
Latency	Less than 6 hours over entire period of qualification campaigns	Average of -4.533 hours over the period of qualification campaigns

Epoch bias	± 50 ms for 75% of the data delivered over the entire period of qualification campaign	Average of 947.545 ms over the period of qualification campaigns, after ignoring gross and statistical outlier measurements from analysis
Epoch bias stability	± 30 ms between average of each individual night and average of the entire qualification campaign	+2 to +12 ms between average of each individual qualification night and average of the entire qualification campaigns
Astrometric accuracy	Less than 1 arcsec RMS for 75% of data delivered over entire period of qualification campaign	2.333 arcsec RMS over the period of validation and qualification campaigns, after ignoring gross and statistical outlier measurements from analysis and considering residuals in 0 to 20 arcsec range
Miss-correlation	Less than 10% of data delivered from a given observation night	0 % as no false positives were identified for the TRK-N targets' data

An observation campaign conducted by AWARE on July 31, 2023, was deemed successful, as all the objectives of the validation process were achieved, and an adequate amount of reduced data was delivered to the Expert Centre. The first attempt to qualify the sensor, conducted on August 9, 2023, was unsuccessful due to technical issues. However, a subsequent attempt on December 12, 2023, proved successful, with a sufficient volume of data collected and feedback provided to the operator. Favourable weather conditions enabled two additional qualification campaigns on December 13 and 14, 2023. Both campaigns were successful, yielding the required data volume for thorough analysis. In particular, from Table 16 it can be seen that:

- **Latency:** The pipeline demonstrated outstanding performance in data latency, delivering results on average 4.533 hours ahead of the required 6-hour threshold. This capability highlights the efficiency of the system in processing and transmitting data within tight timeframes.
- **Epoch Bias:** The baseline requirement of ± 50 ms for 75% of delivered data was not met, with an observed average bias of 947.545 ms. While this value includes corrections for statistical outliers, it indicates a need for enhancements in the system's timing synchronization. In March 2023, it was observed that the time bias of the

AWARE cameras was approximately 1 second. An initial attempt was made to correct this 1-second bias to determine if it would reduce the astrometric error, as shown in Figure 98. The analysis confirmed an issue with the sensor's timestamps, which was further validated through collaboration with the manufacturer and ESA Expert Centre.

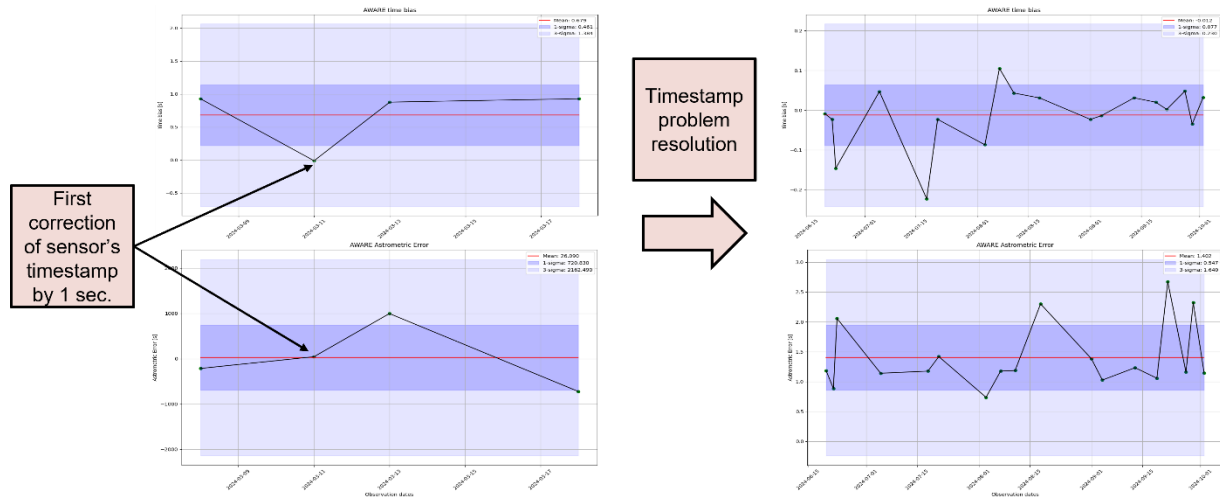


Figure 98. Initial attempt to correct AWARE time-bias by 1 sec.

- **Epoch Bias Stability:** Stability of epoch bias was observed within the range of +2 to +12 ms between nightly averages and the overall campaign average, comfortably meeting the baseline requirement of ± 30 ms. This result demonstrates the system's temporal consistency across the qualification period.
- **Astrometric Accuracy:** The telescope achieved an astrometric accuracy of 2.333 arcseconds RMS, which exceeds the baseline requirement of less than 1 arcsecond RMS. This level of accuracy, even after excluding gross outliers and focusing on residuals within the 0 to 20 arcsecond range, indicates the need for further refinement in the optical and data analysis pipelines.
- **Miss-Correlation:** The system achieved 0% miss-correlation, significantly surpassing the requirement of less than 10%. This indicates a high level of reliability in detecting and correlating observed objects, with no false positives.

Overall, the campaign validated several strengths of the pipeline, such as its latency and miss-correlation performance, while identifying key areas for improvement, including epoch bias accuracy and astrometric precision.

7.2. Mini SURGE validation and calibration campaign

Results obtained from the observations and analysis are shown in Figure 99, in which are displayed the geostationary satellites visible from the observatory's cameras. Magnifications are proposed on one area of the image to allow better visualization.

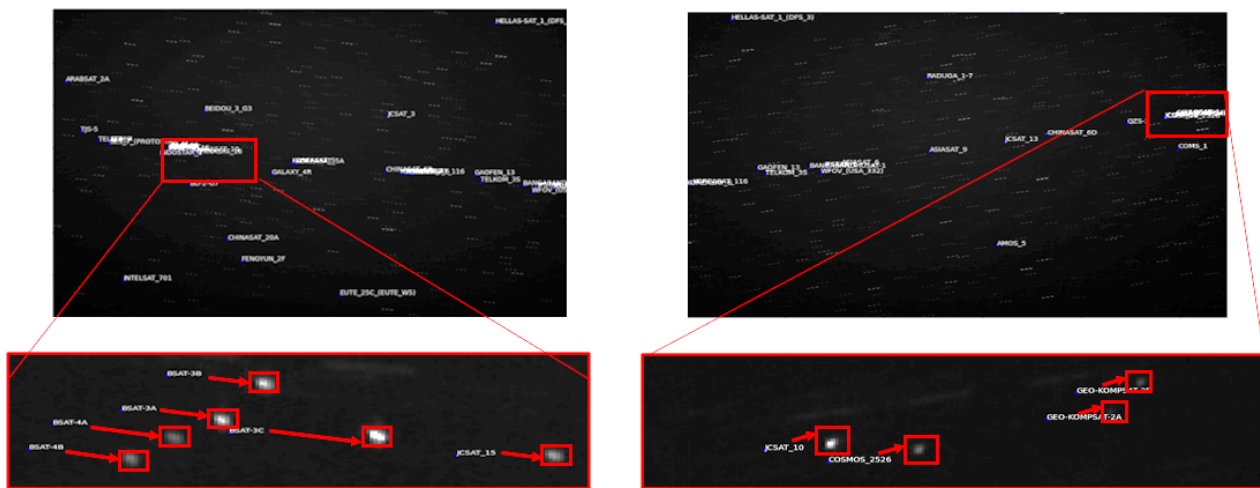


Figure 99. Geostationary satellites camera A (left) and camera B (right)

Figure 100 presents an interesting image: three different targets have been observed simultaneously. The objects are TITAN 34B AGENA D R/B, BREEZE-M DEB and CHINASAT 6B (OR KOREASAT 7).

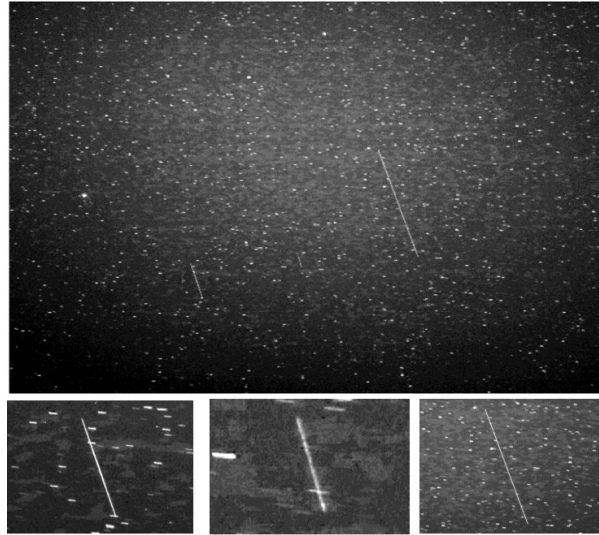


Figure 100. Operative satellites and space debris

Figure 101 shows the composite image by the sum of 13 consecutive frames. The sum allows to get the whole passage of a LEO satellite observed by mini-SURGE. Moreover, a slight movement of another object can be noticed, that appears to be an object in a very high eccentricity orbit (HEO), with 32300 km of apogee.

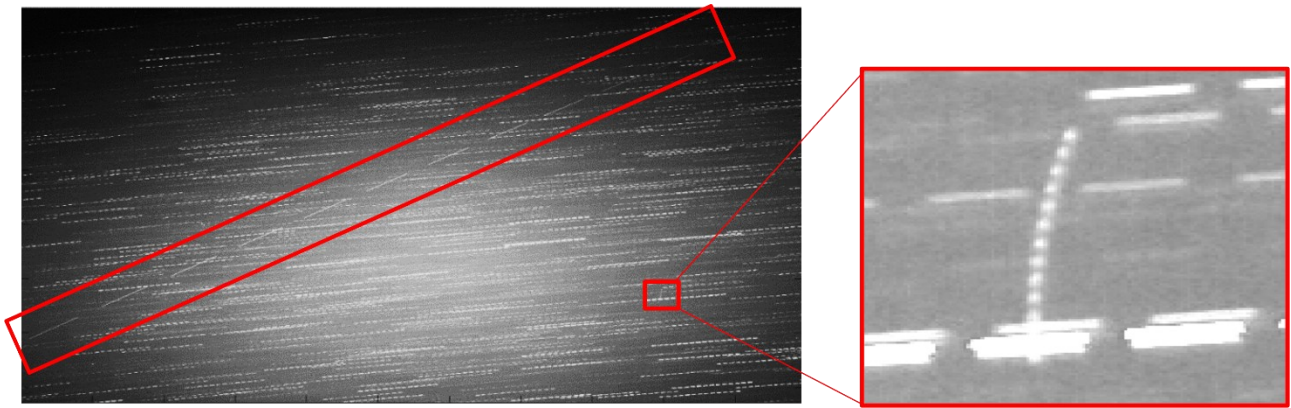


Figure 101. Space debris in LEO: CZ-3C R/B and HEO object: BLOCK DM-SL R/B (right), sum of 13 images

The calibration campaign for the observation system mini-SURGE has been carried out from February 14 2023, to May 5 2023. The main objectives were to select an optimal acquisition setup and to test the accuracy and reliability of the data produced by the measurements process. The campaign has focused on the observation of two satellites with known ephemerides that are constantly visible from the two cameras that make up the system. The chosen objects that release the ephemeris in SP3 format were respectively BD-2-G7 (Norad ID

41586) and QZS-3 (Norad ID 42917). The calibration has produced the computation of a time bias of -0.002734 seconds for camera A and -0.095940 seconds for camera B. Further relevant information, which are the Root Mean Square (RMS) of RA and Dec, are outlined with Table 17.

Table 17. Principal information on Time Calibration of camera A and B of mini-SURGE.

	CAMERA A	CAMERA B
SP3 SATELLITE ID	41586	42917
TIME BIAS	-0.002734 s	-0.095940 s
RMS RA	4.390107e-04	3.920726e-04
RMS DEC	3.474111e-04	3.325040e-04

These results have been used during the analysis of all the geostationary objects that have been observing with mini-SURGE, to improve the quality of the TDM delivered by the data analysis process. The outcomes of the calibration campaign can be summarized by the graphs reported in Figure 102 and Figure 103, respectively for camera A and camera B. Each figure contains the details explained as follows. The graphs in the upper part of the figures show the RA/Dec graphs for Observed versus SP3 Computed measurements. The graphs on the left of the lower part of the figures show the RA and Dec errors for Observed measurements with respect to the SP3 computed measurements. The graphs on the right of the lower part of the figures show the covariance ellipsoids resulting from the comparison of the measures produced by the analysis on the observed data and the measures provided from the available ephemeris.

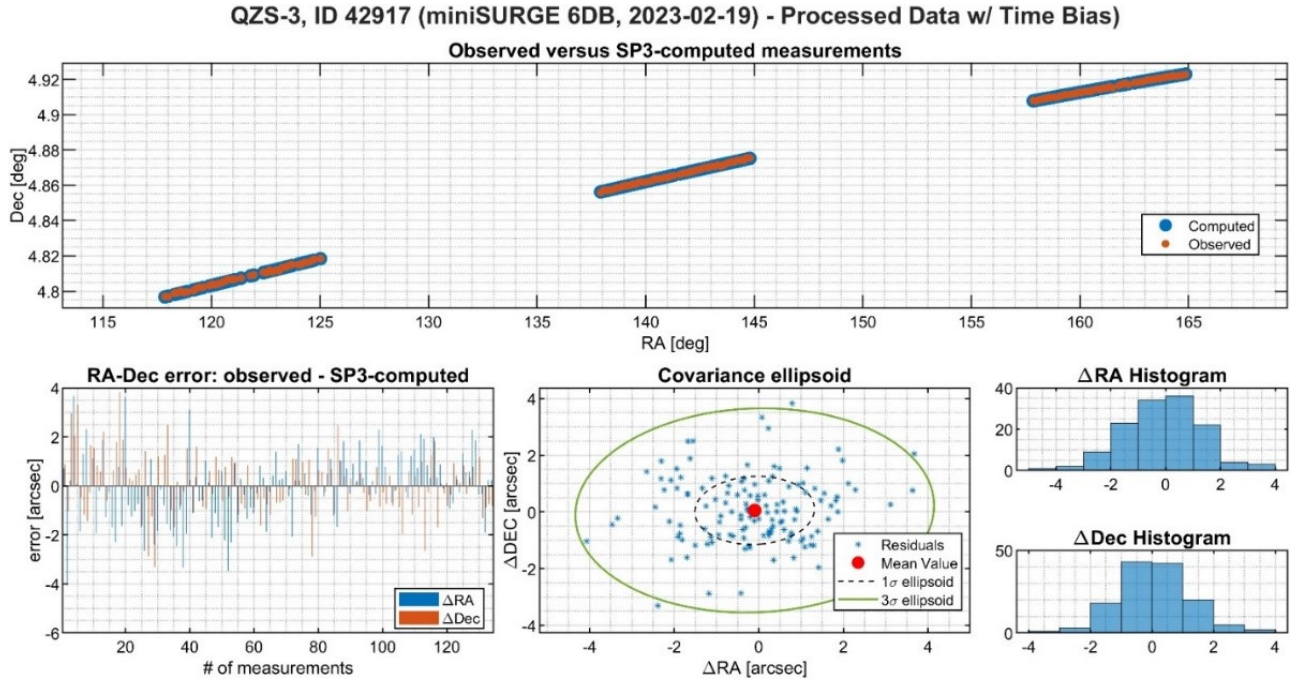


Figure 102. Calibration results for camera A

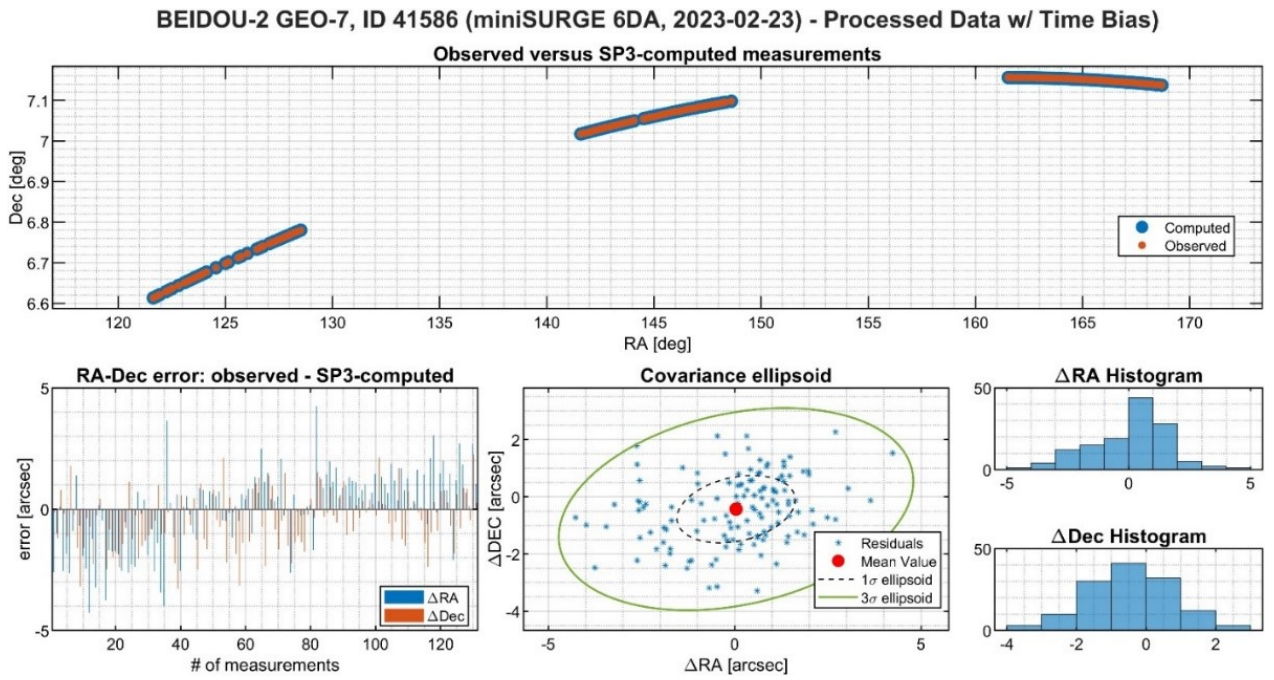


Figure 103. Calibration results for camera B

8. Light curve inversion

The determination of the attitude is fundamental to understand the behaviour of objects in orbit, especially for those not controlled and in the re-entry phase. The sunlight backscattered by orbiting objects and captured by ground-based observatories is influenced by various factors, including attitude, shape, materials of the satellite itself, and the phase angle [34]. These aspects are of great significance as they can have a substantial impact on the amount of light reflected or emitted by the satellite, ultimately reaching the observer on Earth.

The position of the satellite's reflective or emitting surfaces relative to the observer can determine how much of its light is detected. For instance, when the satellite is oriented with its reflective surfaces toward the observer, the perceived brightness will be greater compared to when the reflective surfaces are oriented differently. Another aspect to take into account is the shape of the satellite. The distribution of reflected light can vary depending on its overall geometry and the arrangement of solar panels, antennas, and other components. Satellites with irregular shapes or specific surface details can produce variations in observed brightness on Earth, as these components can act as reflectors or absorbers. In specific spectral regions, the materials employed in the satellite assembly can be more or less reflective or emissive, while other components may be good absorbers. The selection of materials for elements like solar panels or antennas can affect the satellite's reflection in a particular bandwidth and, as a result, the observed brightness.

One way to obtain the characterization information is through the light curves, which represent the change in brightness over time of the object. The reflected brightness received by an observer depends both on the geometry of the observation, therefore on the relative position between observer, object and Sun, but also on the properties of the object such as its attitude, its materials and its shape. Furthermore, light curves, are a technique useful to determine rotation or tumbling rates, as well as their temporal changes.

The first application in which light curves were widely used was to recover information on the shape of asteroids using different techniques [35]-[38]. In this case, simplifying assumptions can be used as asteroids usually have a rotation of the main axis and smooth surfaces made up of a single surface material, which greatly simplifies the inversion of their light curves. As for man-made space objects, such as satellites and space debris, many have a controlled attitude, which simplifies the problem of reversing their light curve. In general [39][41], it has been shown that no principal axis attitude movement can be assumed for uncontrolled spatial objects.

The light curve approach can be used for three different applications:

- The first aims to obtain information on materials. Lynch et al. [42], Seitzer et al. [43] and Schildknecht et al. [44]-[46] analyzed respectively: GEO satellite surface material properties, classified GEO debris based on their size and color, and performed color photometry to distinguish GEO debris based on material types.
- The second is focusing on the study of the space objects tracklets and correlating with a priori knowledge. Cowardin et al. [47] compared optical measurement of Titan fragments with laboratory results to obtain the best match result. Scott et al. [48] established a light curve catalogue based on satellite bus types and made the comparison to differentiate objects.
- The third is based on the directly shape inversion. Hall et al. [49] presented various methods of directly inverting the light curves of spatial objects in order to identify their approximate shape and attitude. To increase the accuracy of the results it was necessary to combine the data obtained with the light curves with the propagation of the orbit, since the problems are coupled [50]. This implies the resolution of a problem with a large number of parameters, which is often not easy to determine. Furfaro et al. [51], to solve this problem, he used machine learning in which Bayesian networks are formed. It is also possible to merge data from different sensors, using an unscented Kalman filter, in order to further increase the accuracy of the estimation of the characterization

information. The latter method was proposed by Linares et al. [52],[53] who simulated several scenarios with success.

Furthermore Piergentili, Santoni et al. have faced the problem of inversion of the light curves obtained from BVRI photometric observations of GEO [54] objects, and from optical observation of LEO satellite and space debris [55],[56]. For the latter, the observed light-curve is compared with a synthetic one in order to retrieve the object's attitude. Many synthetic light-curves are generated with different initial attitude parameters. The more the synthetic light-curve is similar to the observed one, the greater the likelihood that the corresponding attitude parameter represents the real object's attitude. Later, a genetic algorithm is used to minimize a cost function defined as the difference between the real light-curve and the synthetic one [57],[58].

8.1. Overview of the method

The light curve inversion foresees to compare the light curve obtained thanks to an optical observation with a synthetic one. The synthetic light curve represents the variation of the luminous flux reflected by the object over time, understood as the sum of the pixels of the image simulated using a virtual reality simulator through which the passage of the object over the observatory is reconstructed. Once the observed light curve is recovered from an optical observation, it can be compared with a synthetic one to see their similarity.

The first two operations to be performed to create a synthetic light curve are the orbital and attitude propagation. For these two operations three main hypothesis are considered, the TLE is representative of the orbit, the orbit and the attitude are not coupled, and the attitude dynamics do not consider the external torques. These three assumptions permit to speed up the simulation procedure because the orbital propagation can be performed only once, and the attitude propagator integrates only the Euler equations. As mentioned in the

introduction, the TLEs are characterized by low accuracy and short reliability therefore, the TLE closest to the measured time is chosen. The classical Euler equations for a rigid body are used under the acceptable hypothesis of the null external torque since their effects on the object are negligible during the light-curve acquisition period. Many synthetic light curves are generated with different initial attitude parameters. The closer the synthetic light curve is to the observed one, the greater the probability that the corresponding attitude parameter represents the attitude of the real object.

In Figure 104 the architecture of the software is shown, highlighting with different colours the main parts of the software. For each part are indicated the objective, the input and the output.

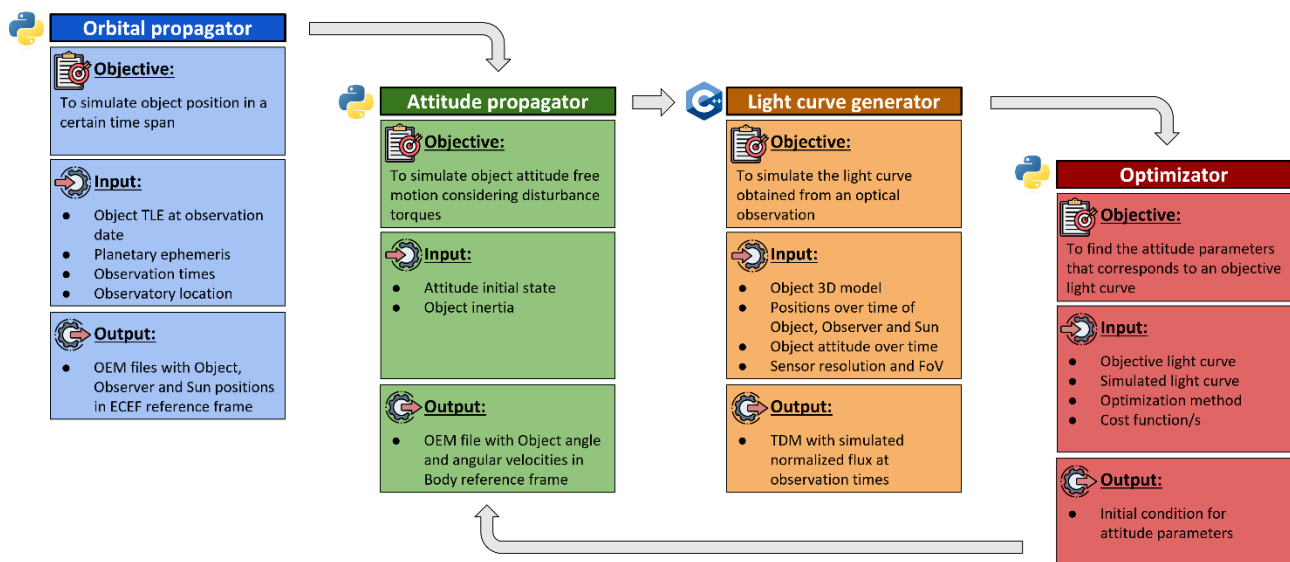


Figure 104. Light curve inversion architecture

8.2. Orbit and attitude propagation

The objective of the orbital propagator is to simulate the position of an object at specific time intervals. To achieve this, it utilizes the object's TLE at the observation date, planetary ephemeris, observation times, and the observatory location. Using these data inputs, the propagator generates several OEM files containing the positions of the object, the observer,

and the Sun, all represented in the ECEF reference frame. Instead, the objective of the attitude propagator is to simulate the free motion of an object's attitude, without considering disturbance torques. The inputs for the attitude propagator are the initial state of the attitude and the object's inertia. The output of the simulation is an OEM file in Body reference frame with Euler angle and the angular velocity components $(\varphi_0, \theta_0, \psi_0, p_0, q_0, r_0)$. at the requested times.

8.3. *Virtual Space Observation Engine (VISONE)*

The virtual reality simulator takes into account numerous parameters and variables, both from an optical and physical point of view, such as atmospheric extinction, the shape and materials of the object, the phase angle between the sun-object-observer and the zones of shadow cast by the object on itself. A bad estimate of these parameters leads to an inaccurate synthetic light curve and therefore to an imprecise determination of the attitude. A specific virtual reality engine is therefore used for space observation simulations: the Virtual Space Observation Engine (VISONE).

The rendering engine recreates a synthetic image of the object as realistically as possible. The outputs of the Physical Engine, the atmospheric extinction and the 3D model of the object are used as inputs in order to recreate the image of the object with also the shadows. The software uses the well-known loader library Assimp [62] making the software able to work with the most of material properties used in the 3D rendering field. The Blinn 'Phong light model [63] is used to recreate lighting conditions, whereas the shadows areas are modeled following the exponential shadow mapping model [64]. All these choices allow to be fast and precise in the light source computation, be they directional or far away, and in the evaluation of the light reflected by the object. In Figure 105 are shown two examples of synthetic images produced by VISONE and showing also the correspondence between the real parameters with the model one.

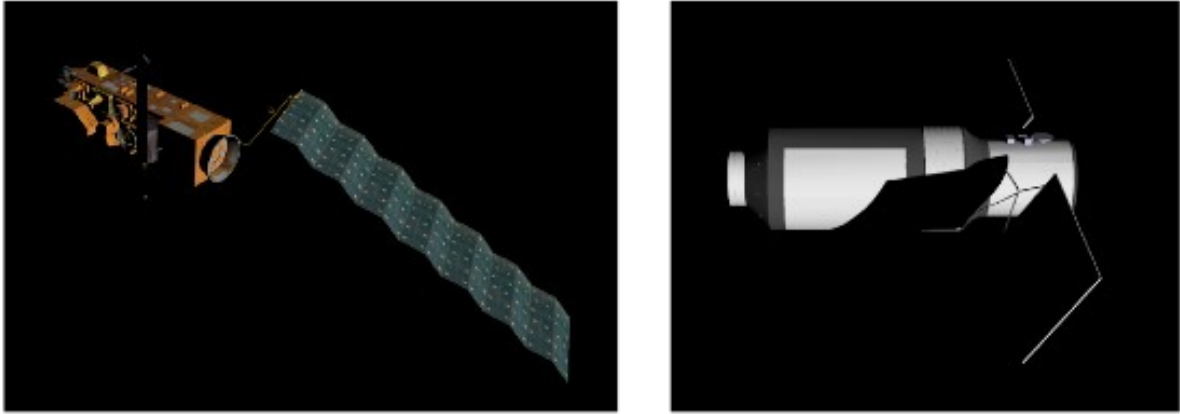


Figure 105. The result of the rendering engine on the 3D model of the Tiangong-1 and Envisat with shadow

8.4. Optimization

For the initial optimization tests, an approach based on a genetic algorithm was chosen. The implementation of the genetic algorithm was carried out using Python and relies on the functionalities provided by the DEAP (Distributed Evolutionary Algorithms in Python) library. This algorithm was selected for its ability to efficiently explore a large solution space and converge toward optimal solutions even in complex scenarios. The steps performed by the genetic algorithm include population initialization, selection of individuals based on fitness, crossover and mutation operations to generate new solutions, and iterative evaluation to refine the population across successive generations. The employed genetic algorithm procedure is:

- GA initially starts with randomly selected solutions (or individuals, all of them combined make up the population) which are randomly spread all across the function.
- Fitness of the individuals (i.e. the value of the cost function) are then calculated and the best individuals are then selected using a selection strategy based on fitness value.
- Selected individuals from population then produce children at the end of each generation, thus passing their fit genes to their children (Crossover).

- Children are similar to parents and suffer from random mutations based on a probability.
- Children from previous generation become population for next generation.
- The process continues for the given number of generations.
- Fittest individual is recorded at the end of all generations, the fittest of them all is the optimum solution.

The employed GA is configured with parameters designed to balance exploration and exploitation, ensuring effective convergence toward optimal solutions. The population size is set at 1000 individuals, providing sufficient genetic diversity and enabling thorough exploration of the search space. The algorithm evolves over 20 generations. Key probabilities include a crossover probability of 0.9 and a mutation probability of 0.05. These values are tuned to maximize exploration through crossover while maintaining a controlled rate of mutation to preserve promising solutions. Additionally, an individual attribute mutation probability of 0.4 allows specific gene alterations during mutation, supporting gradual exploration of new possibilities without overwhelming the population. For crossover, a two-point method is used, where two random crossover points are selected on parent chromosomes, and the genes between these points are swapped. This approach ensures that offspring inherit genetic material from both parents, facilitating the combination of beneficial traits. Mutation is implemented using the bit-flip method, where a random gene is inverted (0 becomes 1 and vice versa), introducing diversity while potentially altering valuable traits. Selection is performed using the roulette wheel method, favoring individuals with higher fitness scores while retaining some chance for less fit individuals to contribute, maintaining diversity. While this method accelerates convergence, it carries a risk of premature convergence if diversity is not adequately maintained.

The optimization process considered three distinct cost functions, each targeting a different aspect of the light curves to improve the overall accuracy of the model. Following are listed these functions along with the main advantages and disadvantages.

- Difference of integrals

The first cost function, the integral difference, focuses on the overall integral of the light curves, measuring the deviation between the predicted and observed intensities across the entire time period.

$$\delta = \left| \int_a^b f(x)dx - \int_a^b g(x)dx \right| \quad (34)$$

Advantages:

- Robustness to Noise: it focuses on the overall shape of the curves and not on the difference of the single values.
- Sensitivity to Shape Differences: is sensitive to both magnitude and shape differences between the curves.

Disadvantages:

- Not consider the Phase Difference: if one curve is shifted by a constant, the integral difference remains the same.
- Sensitivity to Outliers: can be sensitive to outliers in the data, which can distort the similarity measure.

- Spearman rank correlation

The second cost function, Spearman correlation, is designed to evaluate the similarity between the light curves in terms of their shape and pattern, using a correlation-based approach. This function quantifies how well the predicted and observed light curves align in terms of their temporal variations, providing a measure of the consistency of the model with the actual data. It is particularly useful when the goal is to capture the periodicity or other similar characteristics in the light curves.

$$\delta = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)} \quad (35)$$

Advantages:

- Robustness to non-normal data: is a non-parametric measure, meaning it does not make assumptions about the distribution of the data.
- Sensitivity to monotonic changes: is sensitive if one curve increases or decreases consistently relative to the other.

Disadvantages:

- Insensitivity to Scale: if one curve is multiplied by a constant, the correlation coefficient remains the same.
- Not consider Distance between Points: two curves with the same shape but with differently spaced points can have the same correlation coefficient.

- FFT dissimilarity

Finally, the FFT dissimilarity cost function uses the Fast Fourier Transform (FFT) to compare the frequency components of the predicted and observed light curves. This function helps to identify discrepancies in the frequency domain, which can be crucial when analyzing periodic signals or oscillations.

$$\delta = \sum \frac{(|X(f)| - |G(f)|)^2}{|||X(f)| - |G(f)|||^2} \quad (36)$$

Advantages:

- Sensitivity to Frequency Characteristics: useful for identifying similarities or differences between curves that have similar shapes in time but differences in their emphasis on certain frequencies.
- Detection of Phase Differences: detect phase differences between two curves

Disadvantages:

- Loss of temporal information: the FFT transforms a signal from the time domain to the frequency domain, resulting in a loss of temporal information.
- Sensitivity to Noise: can be sensitive to noise present in the data, which can distort the results of the similarity assessment.

Once the cost functions to be optimized are defined, addressing all of them simultaneously requires a multi-objective approach. This necessity arises because the characteristics of the solutions can vary significantly depending on the perspective considered, whether integral behaviour, frequency response, or other criteria. These varying perspectives often lead to trade-offs, as optimizing for one criterion might negatively impact another. To effectively balance these competing objectives and identify solutions that provide the best compromises, the Multi-Objective Genetic Algorithm (MOGA) was chosen. MOGA is particularly suited for such scenarios, as it enables the exploration of trade-offs and the identification of non-dominated solutions that represent optimal compromises across all objectives.

The MOGA is tailored for solving multi-objective optimization problems, where multiple objectives must be optimized simultaneously. Unlike single-objective approaches, MOGA seeks to identify a set of solutions that represent the best trade-offs among competing objectives, rather than focusing on a single optimal solution. This approach enables decision-makers to choose from a variety of solutions depending on specific priorities. The Pareto front is a key concept in multi-objective optimization, representing the set of non-dominated solutions (Figure 106).

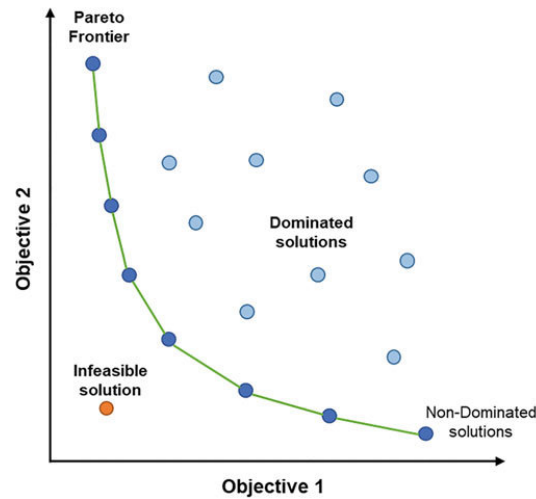


Figure 106. Illustration of Pareto optimization

A solution is considered non-dominated if no other solution can improve one objective without degrading at least one other. These solutions illustrate the trade-offs between objectives and guide the optimization process towards achieving a balance across all goals. The key differences between MOGA and GA are:

- **Objective Handling:** MOGA explicitly optimizes multiple objectives simultaneously, while traditional GA are generally designed for single-objective problems.
- **Solution Output:** MOGA generates a diverse set of solutions along the Pareto front, enabling a broader exploration of trade-offs, whereas GA typically converges to a single optimal solution.
- **Search Strategy:** MOGA's search is directed toward the Pareto front, ensuring a comprehensive evaluation of trade-offs. In contrast, GA may struggle with multi-objective problems, often converging prematurely to suboptimal solutions.
- By integrating these features, MOGA effectively addresses the complexities of multi-objective optimization, providing a robust framework for identifying balanced solutions across competing objectives.

8.5. Simulation test

To compare different configurations of the Genetic Algorithm, it is crucial to ensure that the initial population remains consistent across all configurations. This consistency eliminates the influence of random initialization on the optimization process, allowing for a fair assessment of the impact of different configuration parameters. In the context of random number generation, a seed is a starting value used to initialize a random number generator algorithm. The seed determines the sequence of random numbers that will be generated by the algorithm. Using a fixed seed for generating the initial population achieves this consistency by deterministically producing the same sequence of individuals for each configuration. This ensures that the optimization process starts from the same starting point for all configurations, allowing for a more accurate comparison of their performance.

Moreover, Genetic Algorithms typically operate on floating-point numbers, further expanding the vastness of the solution space. The continuous nature of the parameters introduces an infinite number of possible combinations within each dimension, exponentially increasing the overall size of the search space.

Lower Bound: [-180.000, -180.000, -180.000, -10.000, -10.000, -10.000]

Upper Bound: [+180.000, +180.000, +180.000, +10.000, +10.000, +10.000]

This parameter search space implies a vast and extensive range of potential solutions. With six dimensions, each parameter can assume values within a broad interval, leading to an immense number of possible combinations. Transitioning from a continuous floating-point search space to a discrete one involves quantizing the parameter values into a finite set of integers.

Lower Bound: [-180000, -180000, -180000, -10000, -10000, -10000]

Upper Bound: [+180000, +180000, +180000, +10000, +10000, +10000]

This transformation effectively reduces the number of potential solutions, making the search space more manageable.

Finally, the simulation input are:

- Observatory: SCUDO
- Observation duration: 1 min
- Number of times: 60
- Lower Bound: [-180,-180,-180,-10,-10,-10]
- Upper Bound: [+180,+180,+180,+10,+10,+10]
- Inertia = [2333.0, 6333.0, 500.0]
- Attitude to find: $\theta = [0.000, 0.000, 0.000]$ and $\omega = [5.000, 0.000, 0.000]$

In Figure 107 is shown the rendered model of the reference object and in Figure 108 the light curve produced used the proposed initial condition.



Figure 107. 3D Model of SL-14 R/B (18340)

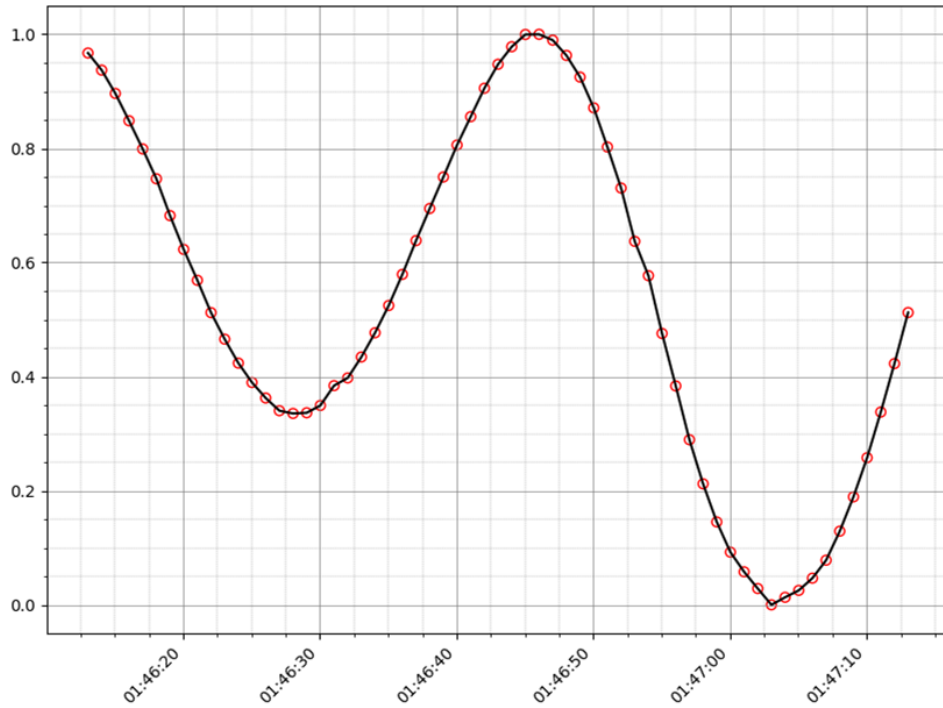


Figure 108. Simulated light curve (objective)

The optimization was performed by evaluating each of the three cost functions separately to assess the convergence of the optimization process and to compare the objectives with the retrieved light curves. Figure 109 shows the results of the optimization for the different cases.

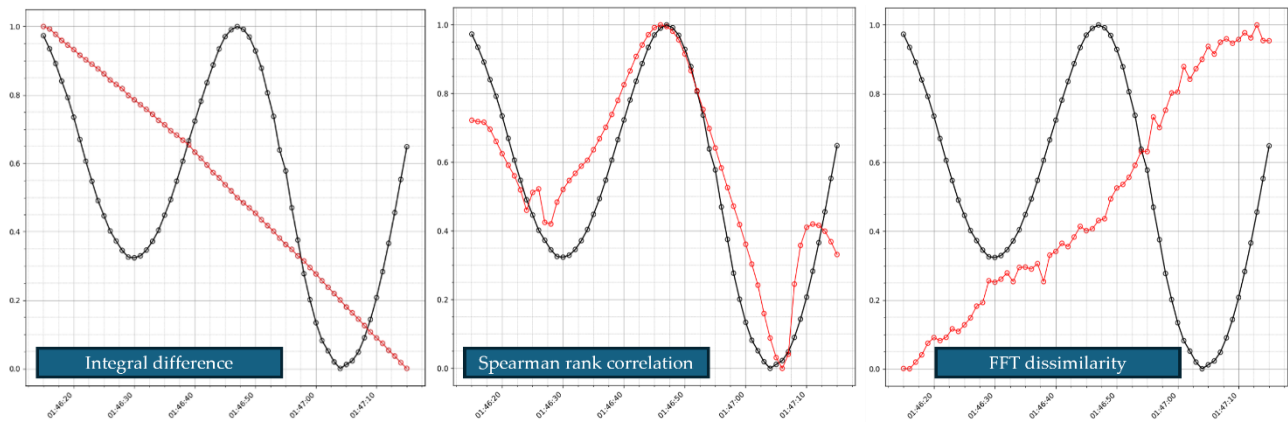


Figure 109. Comparison between integral difference (left), Spearman rank correlation (center) and FFT dissimilarity (right) cost functions

None of the three individual cases led to a satisfactory optimization. All three optimizations ran for just over an hour and a half, but each of the cost functions, which consider different aspects of the light curves, failed to produce meaningful results when optimized separately.

The separation of the cost functions did not allow for a balanced optimization of the multiple objectives. Therefore, in Figure 110, the optimization process using MOGA, which considers all three cost functions simultaneously, is presented. This approach allowed for a more comprehensive optimization, taking into account the trade-offs between all objectives.

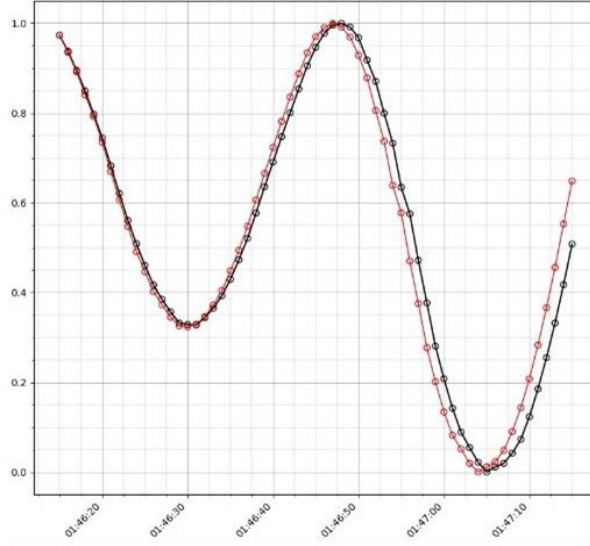


Figure 110. Optimization with MOGA considering simultaneously integral difference, Spearman rank correlation and FFT dissimilarity

In this case, the optimization achieved good results, with the residuals showing a small deviation of $\delta = [0.058, -0.982, 0.000]$, indicating a close match between the predicted and observed data. The optimization process took 6123 seconds, or approximately 1 hour and 42 minutes, which is a reasonable execution time for this level of complexity. The attitude parameters were successfully identified, with the calculated values for the angles $\theta = [0.000, 0.000, 0.000]$ and the angular velocities $\omega = [5.122, 0.000, 0.001]$. These values closely match the target attitude parameters, which were $\theta = [0.000, 0.000, 0.000]$ and $\omega = [5.000, 0.000, 0.000]$, demonstrating the effectiveness of the optimization in finding a solution that aligns well with the desired outcome.

8.6. Real light curve inversion

The same object used for the simulated case was also used for the real case. The light curve was acquired with SCUDO observatory during the night of 2024-05-04. The optimization

results show that the residuals are $\delta = [113.263, 0.039, 0.838]$, indicating a good overall fit with some deviations in the model. The execution time for this process was 6123 seconds, or 1 hour and 42 minutes. The attitude parameters were found with the quaternion values $q = [0.5498, 0.4421, -0.434, 0.5063]$, and the Euler angles $\theta = [93.227, -1.797, -79.304]$ with angular velocities $\omega = [1.312, 0.745, 20.100]$. The simulated light curve and the real one are shown in Figure 111.

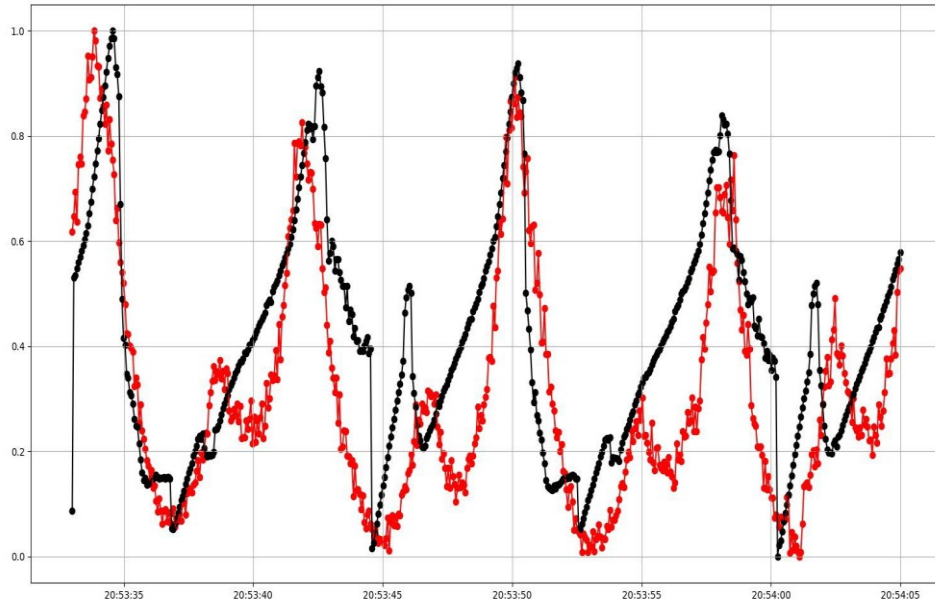


Figure 111. Simulated versus real light curve

While the two light curves are not perfectly identical, the similarities are evident, with the peaks in the observed and predicted curves matching quite well. The discrepancies can be attributed to several factors, including the inaccurate knowledge of the object's 3D model, such as its dimensions, inertia, components, and materials. These variations can influence the light curve due to the way the object interacts with light. Despite these challenges, the optimization successfully found a compatible attitude solution, demonstrating that the two light curves, while not identical, are sufficiently similar to confirm the validity of the model under the given conditions.

9. Feasible options to study Molniya population of space debris

Following the development of software for image and data analysis, the next step involved testing its effectiveness in real-world observation scenarios. To this end, an observational campaign was conducted to validate the pipeline under operating conditions. This campaign was organized within the framework of an international observational effort involving multiple space agencies, providing an excellent opportunity to assess the software's performance in a collaborative and highly demanding environment.

9.1. Introduction

Initial finding from previous activities of the Working Group 1 (WG1) of the Inter-Agency Space Debris Coordination Committee (IADC) in the Internal Task 34.1 (IT 34.1) shown that MASTER and ORDEM models need more information (orbital dynamics, number, spatial distribution, ...) for Molniya population. Available limited observation data show that population of objects having apogee over the Southern hemisphere is already large enough (not less than 40% of the entire population at such orbits). Measurements of space debris residing at Molniya-type orbits or having transited to orbits like Molniya-type, with apogee over near-equatorial latitudes or the Southern hemisphere is of large interest for modelling purposes. Dedicated strategies have to be studied, also based on archive dataset, and implemented to permit a comprehensive observation campaign. Target regions where does exist a high density of Molniya Resident Objects will be considered. Different methods to carry on the measurement campaign will be used to optimize the capabilities of different participants.

9.2. IT 34.1 *history until 2022*

In 2016, during the 34th IADC held in Oxford, leaders Tommaso Cardona (ASI) and Phil Herridge (UKSA) led discussions on a proposal for an internal task aimed at preparing an observation campaign for Molniya orbits. Various techniques and options for the campaign were considered during these meetings. A report on these activities was scheduled for January 2017, with the goal of proposing an Action Item (AI) at the 35th IADC.

In 2017, at the 35th IADC in Darmstadt, the leaders of the internal task presented a strategy to identify, for each instrument, the part of the sky with the highest density of catalogued Molniya objects. This led to extensive discussions on how to correlate the targets and distinguish them from background objects. Further research was planned by the Principal Investigator (PI) leading team regarding the angular velocities and apparent brightness distribution of the observed objects. During the same meeting, ROSCOSMOS shared information on the currently known population of tracked debris in Molniya orbits, proposing to use this information for better preparation for the potential observation campaign. However, it was deemed too early to establish a new Action Item at that time, with the decision to revisit the issue at the next IADC in the hope of establishing a new AI in the future.

In 2018, during the 36th IADC in Tsukuba, Alexander Lapshin from ROSCOSMOS presented a report on the characteristics of the orbit and the photometry of 234 Molniya objects catalogued by Space-Track, along with 118 objects that were not catalogued. The main difference identified between catalogued and uncatalogued objects was the Area to Mass Ratio: catalogued objects had a ratio of less than 0.03, while uncatalogued objects had a ratio greater than 0.03. Further studies on these objects were planned.

In 2019, at the 37th IADC in Rome, was highlighted that the known population of debris in Molniya orbits is very poor compared to other orbital regimes and current space debris models do not accurately incorporate evolutionary trends or the population of these objects.

The extensive evolution of Molniya orbits has highlighted the need for a joint observation campaign in both northern and southern locations. These points were discussed with WG2, which supported the internal task and the potential future campaign within the framework of a new Action Item (AI). The proper selection of an object for the campaign is of high importance to ensure its accessibility by optical and, if possible, RADAR sensors. It was also discussed a possible future campaign in the framework of a new AI and to conduct a re-entry campaign for an object in Molniya-type decaying orbit. It was noticed that a significant coordination will be required amongst agencies to immediately update orbits for follow-up observations, and a proper selection of an object for the campaign is of high importance.

9.3. Objectives description

In 2022, during the 40th IADC in Jeju, the task was reactivated, and both the coordinators and the objectives of this internal task were updated, with Lorenzo Mariani (ASI) becoming the new internal task leader and Pascal Richard (CNES) as the co-leader. This IT aims to conduct joint observations of calibration targets with the goal of improving observation strategies, analysis methods, and result refinement, as well as fostering the exchange of findings among participants. Additionally, there is a statistical search for uncatalogued Molniya objects. The primary objective is the accurate orbital determination of Molniya-like target objects to investigate long-term orbital evolution. Simultaneously, a statistical survey for specific Molniya-like objects is planned to understand the trackable and unknown population, to investigate long term orbital dynamics, to improve the existing or to develop new observing techniques and strategies and support forensics of events in Molniya. To fulfil the objectives of this IT, two observational campaigns are required. The first is a series of observations involving 10 objects that must be tracked using the TLE tracking mode for an extended period. The second is a one-week observation campaign during which specific regions of the sky should be observed using the sidereal tracking mode. In particular, the internal task aims to promote:

- Joint observation of calibration target, in order to improve observation strategies, analysis methods and results refinement and to foster findings exchange among participants.
- Statistical search for uncatalogued Molniya objects.
- Accurate orbital determination of some Molniya-like target objects to investigate long term orbital evolution.
- Statistical survey for some target Molniya-like objects aiming to investigate coupling between attitude dynamics and orbit evolution.
- Support forensics of events in Molniya.

In 2023 during the IADC41 meeting, were presented two non-exclusive initiatives for observation campaign, and according to the discussion the schedule of this internal task was updated in:

- The collection of information, 2023 Q1 telecon.
- The execution of a preliminary coordinated test to understand availabilities, capabilities, and catalogued object detectability.
- The planning for a coordinated test, IADC41 in June 2023.
- The execution of a precursor coordinated test for the study of the uncatalogued Molniya population and exchange about findings before the end of 2023 Q4.
- Presentations of the findings of the coordinated test at IADC42.
- The collection of lessons learned, IADC43.

9.4. Molniya population and targets selection

The Molniya orbit is a highly elliptical configuration designed to provide extensive coverage of polar regions. Characterized by high eccentricity, Molniya orbits allow satellites to spend most of their time over the northern latitudes of Earth, where their apogee extends to high latitudes, ensuring continuous communication in these areas. However, this exposed

configuration makes Molniya satellites particularly susceptible to gravitational perturbations, which can accelerate the degradation of their orbits over time. As a result, the typical operational life of a Molniya satellite is approximately 6 years, due to these perturbations that necessitate adjustments and maintenance to maintain mission effectiveness. The main perturbations affecting these satellites are the Earth's gravity gradient, Sun radiation pressure, third body effect and their interaction with the magnetosphere. These forces play a significant role in the dynamics and stability of Molniya satellites. In Figure 112 a representation of the Molniya orbit to show the main perturbances that act on the orbit.

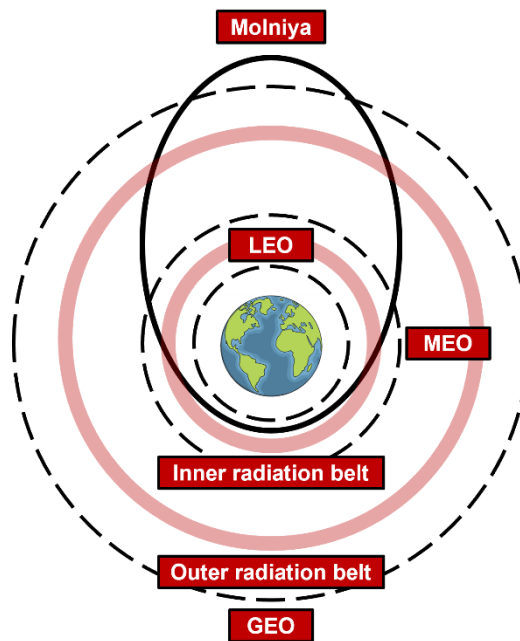


Figure 112. Representation of Molniya orbit

To select the objects in Molniya orbit contained in the NORAD catalogue, some boundaries around the typical Molniya orbit parameters was selected. In particular, the chosen boundaries on the orbital parameters to classify the Molniya-like objects are:

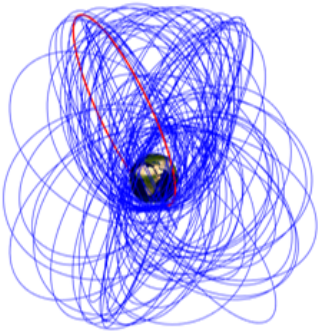
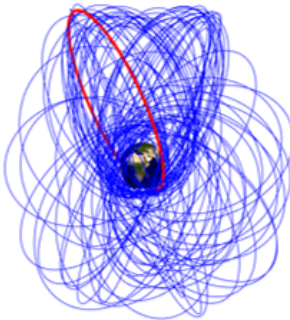
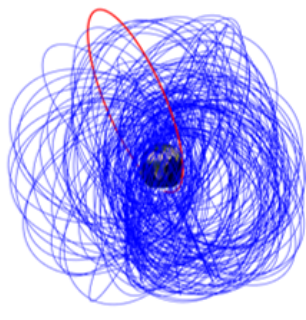
- Inclination [deg]: 67.5 ± 7.5 (typical ~ 62.8 deg)
- Mean Motion [rev/day]: 2 ± 0.5 (typical ~ 2.0 rev/day)
- Eccentricity: 0.65 ± 0.15 (typical ~ 0.72)
- Altitude: 150 km to 40000 km

Applying these constraints to the NORAD public catalogue as of June 2023, 337 objects were extracted, of which 7 were To Be Assigned (TBA) and 3 have a very old TLE. In addition to the previously selected objects, Molniya satellites belonging to old Molniya constellations have been added to the list. These satellite out of the constrains are 13, in particular:

- Molniya-1: 22671, 23420, 24960.
- Molniya-3: 11057, 15738.
- Oko: 6192, 15952, 16527, 17213, 18103, 18701, 19554, 19608.

It is possible to divide these objects in three different categories: satellites related to Molniya mission, rocket bodies and debris. In Table 18 are shown the number, eccentricity, inclination and mean motion ranges and the orbits in ECI reference frame of these objects.

Table 18. Number, eccentricity, inclination and mean motion ranges and the orbits in ECI reference frame of the Molniya-like objects

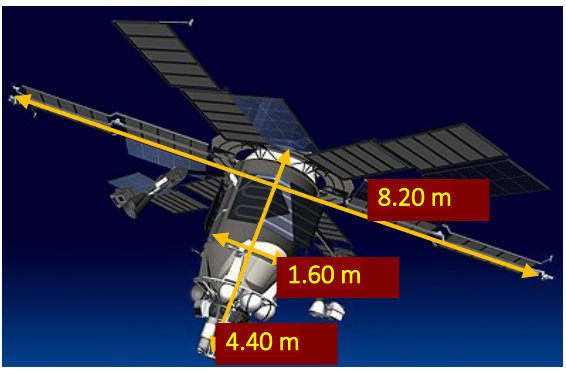
Parameter	Missions	Rocket bodies	Debris
Number	92	106	152
Inclination	61.6 – 72.6 [deg]	61.8 – 72.7 [deg]	61.1 – 74.2 [deg]
Mean Motion	1.98 – 5.63 [rev/day]	1.96 – 2.49 [rev/day]	1.8 – 2.2 [rev/day]
Eccentricity	0.41 – 0.75	0.51 – 0.73	0.50 – 0.77
Orbit			

It can be observed how perturbations have acted differently depending on the type of object. In particular, Table 18 highlights that most objects belonging to missions and rocket bodies have their apogee in the Northern Hemisphere, whereas some of these objects and the majority of debris have shifted their perigee. To clarify the nature of the objects under

discussion, a detailed description of the dimensions and shapes of the selected Molniya objects is provided below.

The Molniya series of satellites, including Molniya 1, 2, and 3, were launched by Russia primarily for military and communication purposes. The Molniya-1 satellites, launched between 1967 and 1975, were among the first in the series and were designed to provide communication capabilities. The Molniya-2 satellites, launched from 1971 to 1977, continued the mission of providing enhanced communication services. The Molniya-3 satellites, spanning launches from 1974 to 2003, extended the capabilities and lifespan of the Molniya series, supporting both military and civilian communication needs. The considered targets of this series are reported in Table 19.

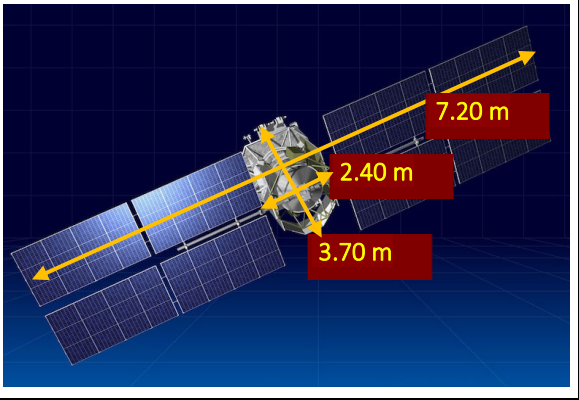
Table 19. Selected targets for the Molniya 1, 2, 3 series

Total targets	34	
Molniya-1	19	
Molniya-2	3	
Molniya-3	12	

The Meridian series (Table 20), launched by Russia for military and communication purposes, includes two main versions. The first version of the Meridian satellites was operational from 2006 to 2014. This was followed by the Meridian-M version, which has been operational from 2019 to 2022. These satellites are intended to replace the two last series of Molniya satellites still in activity.

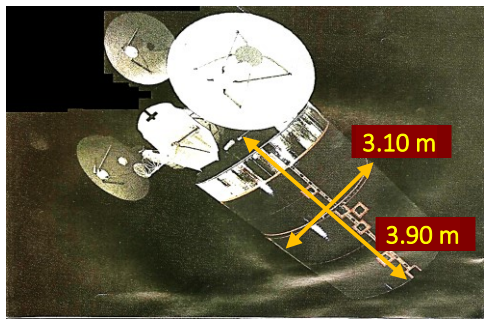
Table 20. Selected targets for the Meridian series

Total targets	7	
---------------	---	--

1 st ver	4	
Meridian M ver	3	
Active	4	

The SDS (Satellite Data System) series, including SDS 1, 2, and 3, were launched by the USA primarily for military and communication purposes. The SDS-1 satellites, operational from 1976 to 1987, initiated the series with a focus on providing secure communication channels for military operations. The SDS-2 satellites, launched between 1989 and 1996, continued this mission, and the SDS-3 series, spanning from 1998 to 2022, further enhanced the capabilities and operational lifespan of the system. Although the TLEs for these satellites are not available. In Table 21 the selected target for the SDS series.

Table 21. Selected targets for the SDS series

Total targets	3	
SDS-1	3	
SDS-2	0	
SDS-3	0	

To understand the evolution of the orbital parameters, Figure 113 compares the orbits of the SDS-1 series in 2019 and 2023. Additionally, Table 22, Table 23 and Table 24 present the evolution of each parameter for each satellite in the series, where it is possible to notice the large evolution of the orbital parameters in only 4 years.

Table 22. Four years orbital parameters evolution for OPS 5805

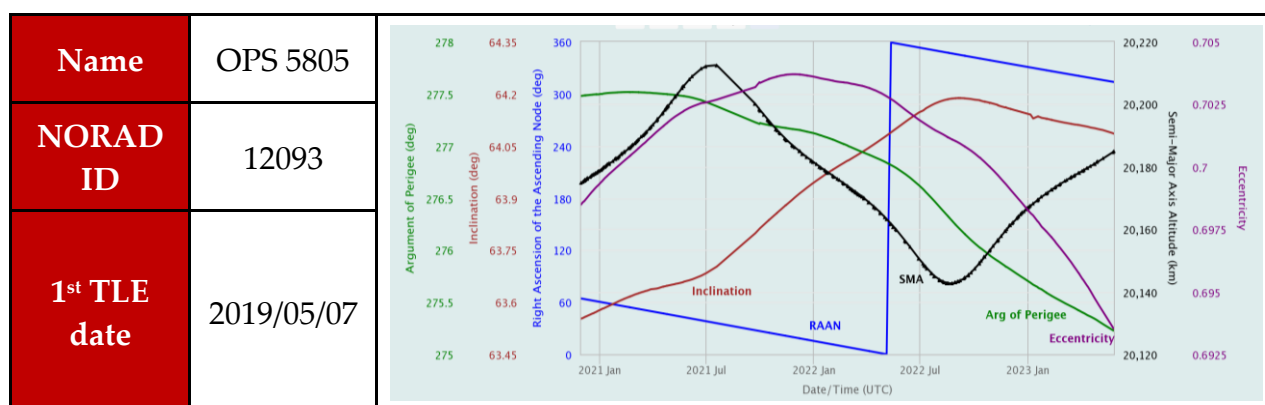


Table 23. Four years orbital parameters evolution for USA 4

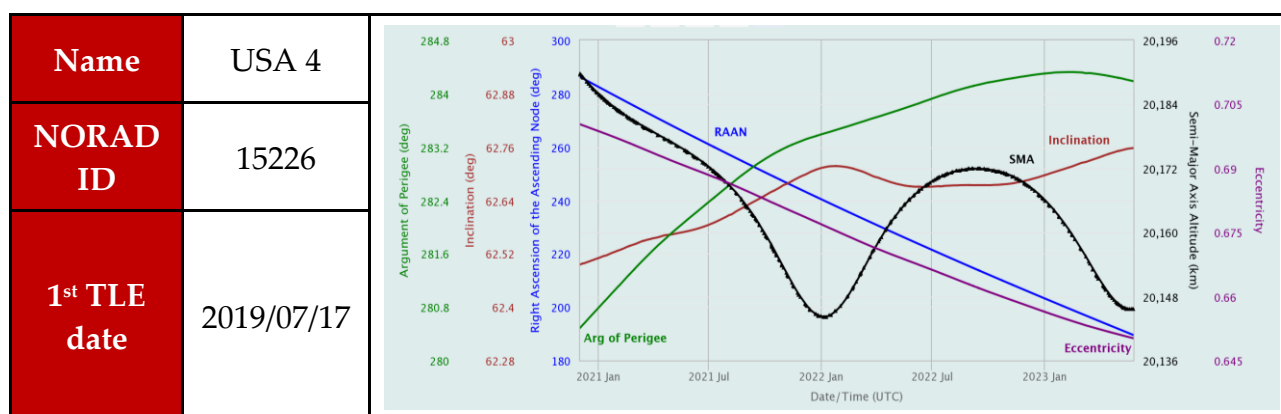


Table 24. Four years orbital parameters evolution for USA 21

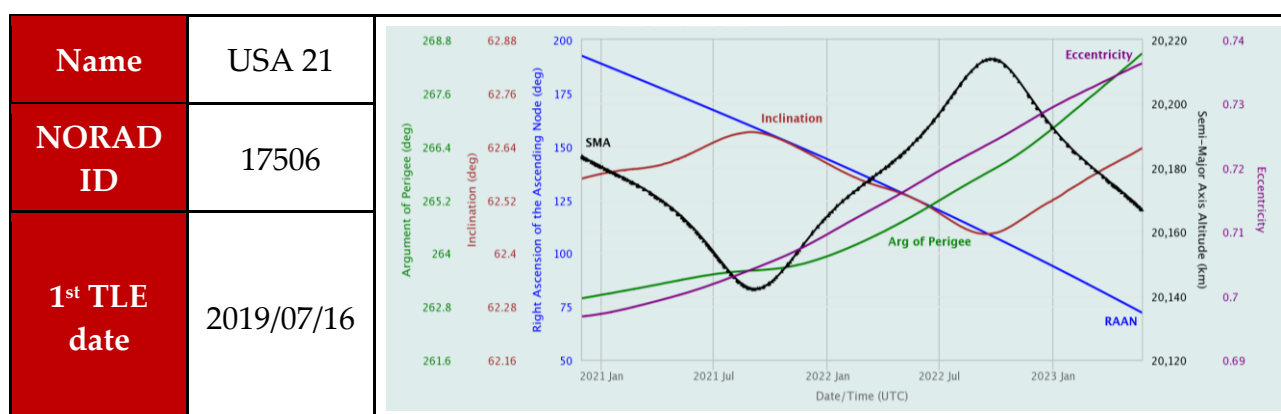




Figure 113. Comparison between TLE sets of 2019 and 2023 for SDS-1 series

The OKO series, launched by Russia for missile early warning purposes, includes various Cosmos satellites operational from 1972 to 2012. This constellation was part of Russia's early warning system designed to detect and track missile launches (Table 25). The OKO satellites were placed in highly elliptical orbits, allowing them to provide extended coverage of the Northern Hemisphere, which was critical for monitoring potential missile threats from the United States and other regions. The system utilized infrared sensors to detect the heat signatures of missile launches, enabling early detection and response to potential nuclear threats during the Cold War era. Notably, some of these satellites are in the re-entry phase, specifically Cosmos with NORAD catalogue numbers 16993, 27409, and 27613.

Table 25. Selected targets for the OKO series

Total targets	48	
Re-entered	33	
Re-entering	3	
Self-destruction	1	

In Figure 114 and Figure 115, the observations of Cosmos 1547 and Cosmos 2084 from the AWARE observatory on May 26, 2023, are shown in two different orbital phases. The first observation is near the apogee, while the second is near the perigee. It is possible to notice the difference in brightness of the two objects due to different observation geometries, in terms of elevation and phase angle. Additionally, the dwell time of the objects on the pixel varies due to their relative speed, which is influenced by their orbital phase.

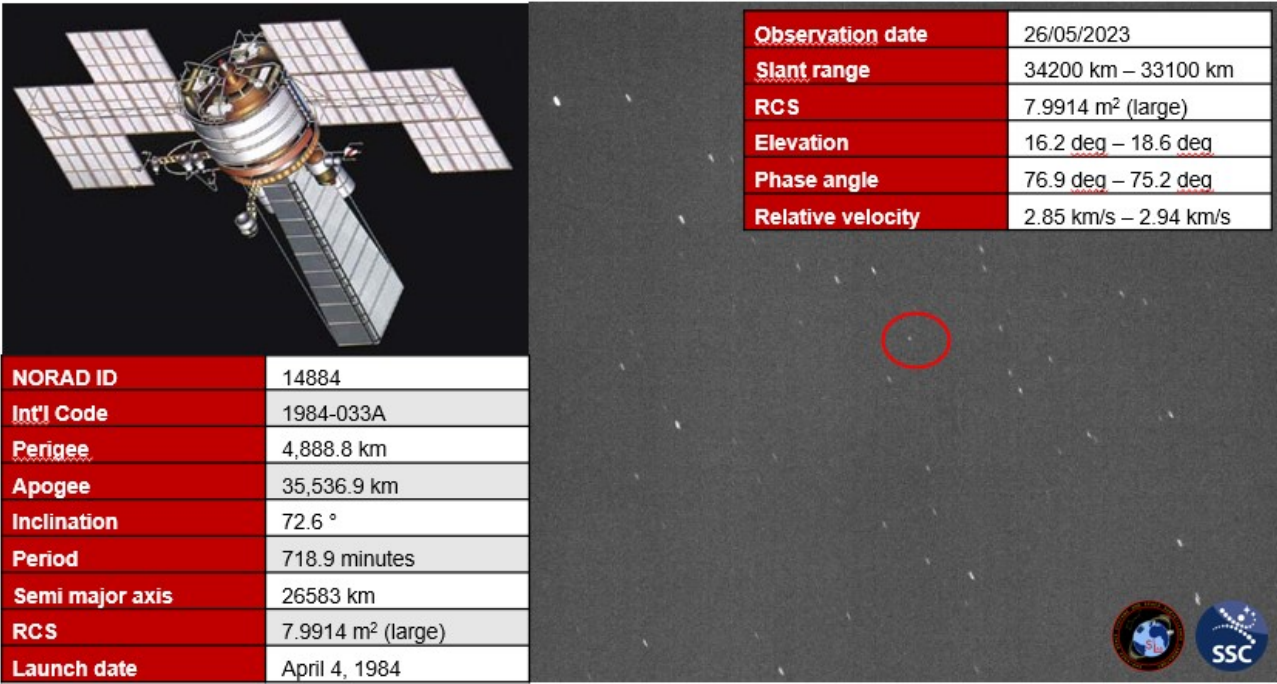


Figure 114. Cosmos 1547 from the AWARE Observatory (AU) on May 26, 2023

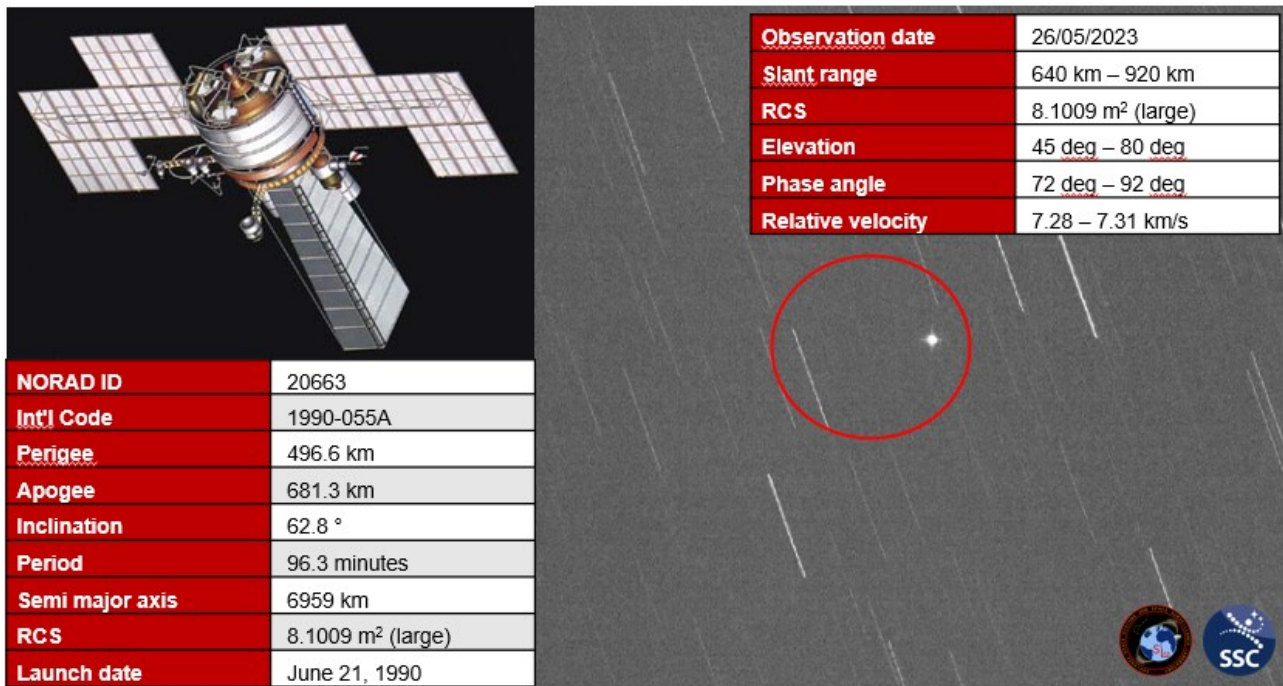


Figure 115. Cosmos 2084 from the AWARE Observatory (AU) on May 26, 2023

Some rocket bodies and debris, which are auxiliary engines, or second stages associated with Molniya satellites, were also added to the list. These 21 objects are in detail:

- SL-12 R/B (auxiliar motor): 16446, 18374, 19170, 19755, 19856, 20081, 20630, 20631, 21012, 21220, 21226, 23402, 23403, 36406, 37143.
- CZ-3B R/B: 43110, 43247
- SL-12 DEB: 42974, 48349, 48417
- USA 125 DEB: 23947

The rocket bodies SL-6 (2nd stage), SL-12 (2nd stage), SL-12 (AUX MOTOR), and SL-26 are components of rockets primarily used by the Russian space industry. The SL-6 and SL-12, also known as Proton-K, were used for launching heavy payloads into low Earth orbit and geostationary orbit. The SL-12 auxiliar motor provides additional thrust and control during the launch phase. The SL-26, or Soyuz-FG, is renowned for crewed missions to the ISS and other unmanned payload launches. In particular, the selected objects are reported in Table 26 and in Figure 116 are shown the typical shape of these objects.

Table 26. Rocket bodies

SL R/B	87	Other R/B	19
SL-6 (2 nd stage)	69	FREGAT	12
SL-12 (2 nd stage)	1	DELTA 4, ATLAS 2A	2
SL-12 (AUX MOTOR)	15	TITAN 34B, AGENA D	3
SL-26	2	CZ-3B	2

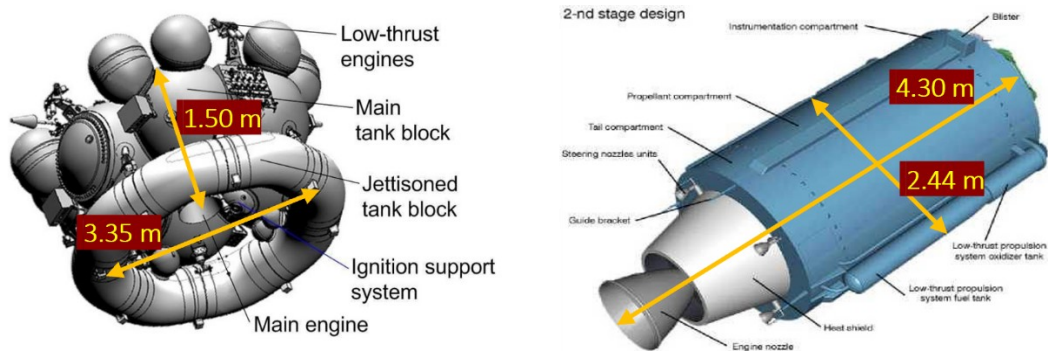


Figure 116. Fregat engine (left) and SL-12 second stage (right)

A particular class of the rocket bodies are the SOZ ullage motor. These motors are used in space propulsion systems to settle propellants in rocket fuel tanks before main engine ignition, ensuring that liquids inside the tanks are properly positioned. This process, known as ullage, is crucial for maintaining stable acceleration and trajectory control of the spacecraft. Figure 117 shows a representation of a typical ullage motor, along with the main dimensions, provided by NASA in [65].

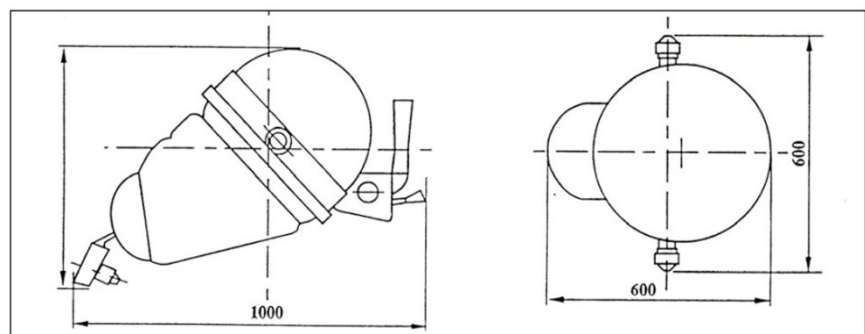
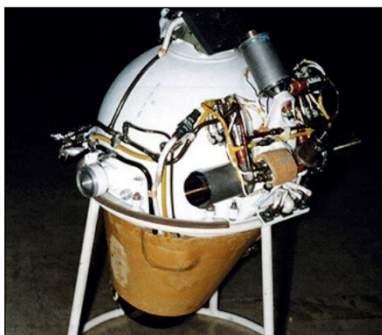


Figure 117. SL-12 auxiliary motor

Due to their relatively small size with respect to the other Molniya assents, these objects can be used to understand the detectability of small object in Molniya orbit. In Figure 118 an example of the observation of three ullage motor performed by SCUDO in the same night and approximately in the same hour.

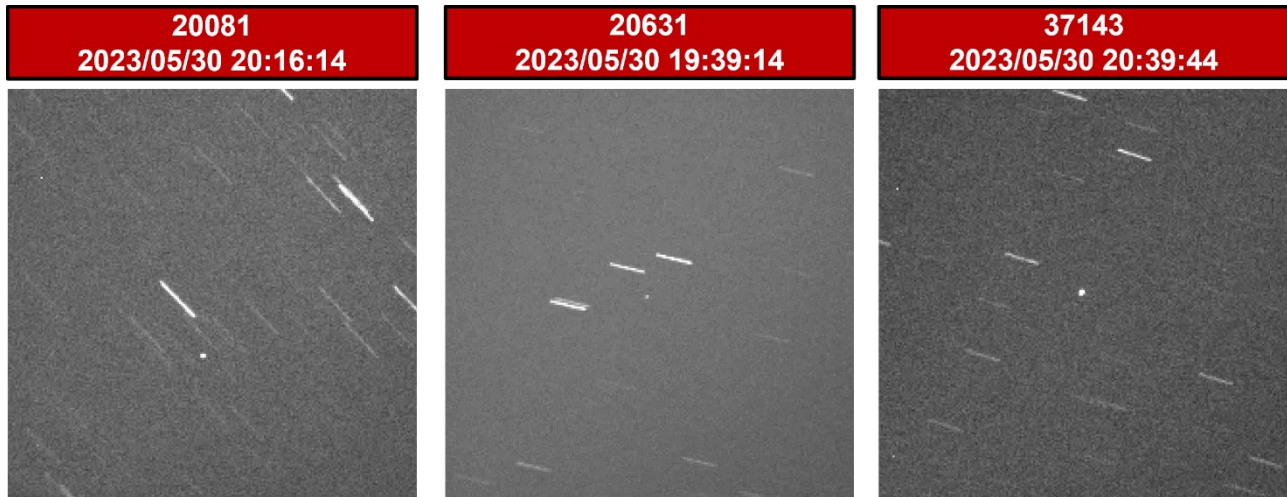


Figure 118. Three SOZ objects observed from SCUDO

The last class of objects are the debris that present a Molniya-like orbit. For these objects no information about shape and/or main dimensions are available, that makes the observation challenging. In Table 27 the satellites from which the debris are generated are listed:

Table 27. Debris

Debris	152
COSMOS	138
SL-6	4
SL-12	3
DELTA 1	1
SOLWIND	2
ARIANE 1	1
THOR ABLESTAR	1
TITAN 34B AGENA	1
USA-125	1

Considering also these targets, a total of 371 objects in the NORAD public catalogue were selected as targets for the observation campaign.

The future space initiatives in Molniya are mainly three. One constellation is Shiyan, designed for agricultural monitoring and space environment observation through an experimental satellite program. Over the period from 2021 to 2025, Shiyan plans to deploy five High Earth Orbit (HEO) satellites, with one already partially operational (NORAD ID: 49258 - SHIYAN 10) and another fully operational (NORAD ID: 54878 - SHIYAN 10 02). Similarly, the Arktika-M constellation aims to monitor Earth's high-latitude regions through remote sensing capabilities and emergency communications. With a planned deployment of five HEO satellites from 2021 to 2025, one satellite is currently operational in orbit (NORAD ID: 47719). Additionally, the Ekspress constellation focuses on enhancing Ku-band coverage over Russia's Far North. Planned initiatives include the launch of four HEO satellites in 2024, followed by eight Geostationary Earth Orbit (GEO) satellites from 2025 to 2030. A representation of the satellite busses is shown in Figure 119.



Figure 119. Shiyan (left), Arktika-M (center) and Ekspress (right) Molniya busses

9.5. Statistical survey observation campaign

The statistical survey observation campaign focused on a set of 10 selected targets, with the observations conducted using TLE tracking between July 2023 and April 2024. The campaign included both astrometric and photometric analyses, with specific requirements for data acquisition at different orbital phases. For the apogee, observations were required to consist of either one series with a minimum of 200 frames or two series with at least 100 frames each. For the perigee, the aim was to collect as many frames as possible in a single

series. For each observation, the output included the observatory coordinates and two TDM files: one containing topocentric right ascension and declination data and the other containing the observed luminous flux.

9.5.1. Description

To determine the Molniya-like targets to observe with the aim of investigate the coupling between attitude dynamics and orbital evolution, 92 Molniya satellites belonging to recent or past constellations were selected. To plan the ASI observations, a preliminary table with the visibilities was created as shown in Figure 120.

SSN	Sat_Name	30-May-2023	31-May-2023	1-June-2023	2-June-2023	3-June-2023	4-June-2023	5-June-2023	6-June-2023	7-June-2023	8-June-2023	9-June-2023	10-June-2023
6192	COSMOS 520												
6916	COSMOS 606												
7376	MOLNIYA 2-10												
11057	MOLNIYA 3-10												
12078	COSMOS 1223												
12907	COSMOS 1030 DEB												
13080	COSMOS 1341												
15350	COSMOS 1604												
16446	SL-12 R/B(AUX MOTOR)												
18374	SL-12 R/B(AUX MOTOR)												
18701	COSMOS 1903												
19170	SL-12 R/B(AUX MOTOR)												
19755	SL-12 R/B(AUX MOTOR)												
19856	SL-12 R/B(AUX MOTOR)												
20081	SL-12 R/B(AUX MOTOR)												
20330	COSMOS 2050												
20596	COSMOS 2076												
20630	SL-12 R/B(AUX MOTOR)												
20631	SL-12 R/B(AUX MOTOR)												
20707	COSMOS 2087												
21012	SL-12 R/B(AUX MOTOR)												
21220	SL-12 R/B(AUX MOTOR)												
21226	SL-12 R/B(AUX MOTOR)												
22321	COSMOS 2232												
22671	MOLNIYA 1-86												
23402	SL-12 R/B(AUX MOTOR)												
23403	SL-12 R/B(AUX MOTOR)												
23947	USA 125 DEB												
24761	COSMOS 2340												
24960	MOLNIYA 1-90												
25327	COSMOS 2351												
27884	COSMOS 917 DEB												
27901	COSMOS 1261 DEB												
36406	SL-12 R/B(AUX MOTOR)												
37143	SL-12 R/B(AUX MOTOR)												
42974	SL-12 DEB												
43110	CZ-38 R/B												
43247	CZ-38 R/B												
48349	SL-12 DEB												
48417	SL-12 DEB												

Figure 120. Extract of the table with the visibilities for the 92 selected target

Once the visible objects are selected it is necessary to evaluate the observation geometry to ensure the object will be detected in the images. Three main parameters were considered to select the most visible objects, the range, the elevation and the phase angle. In Figure 121 is shown a graph in which are displayed the ground track of the Molniya objects with different colours to highlight the parameters.

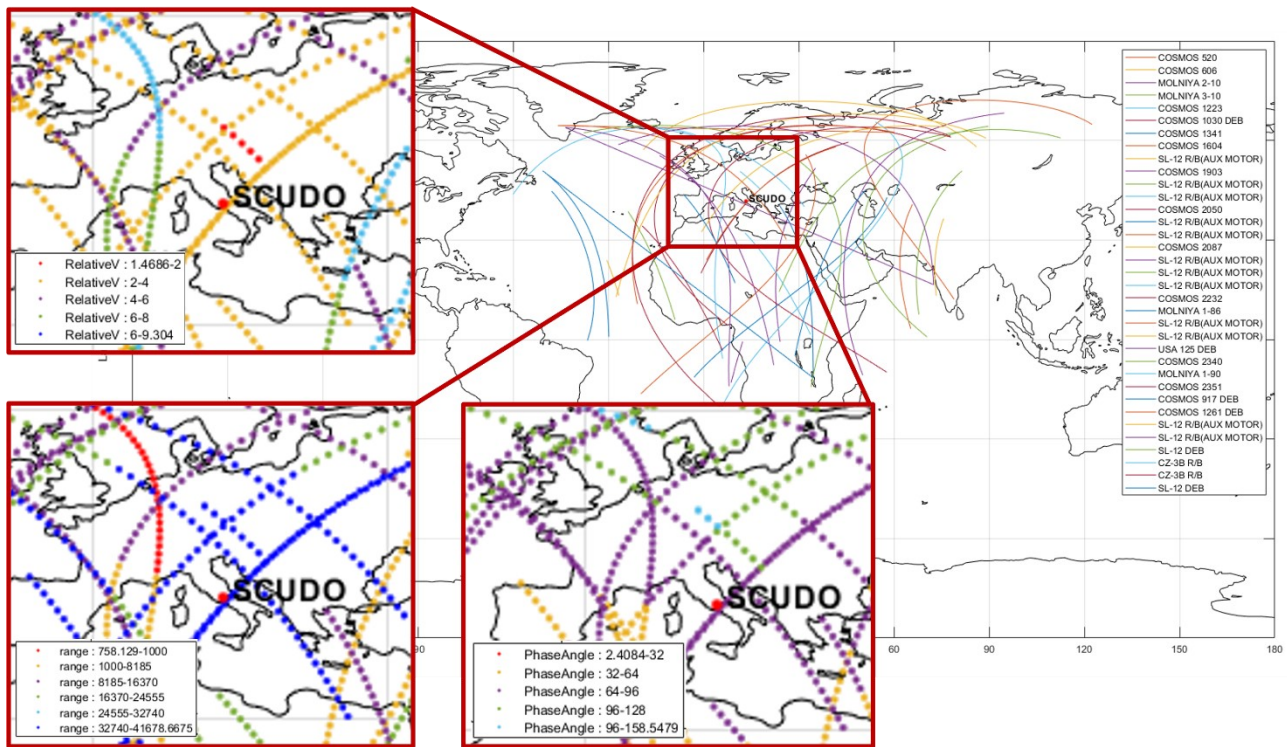


Figure 121. Visual representation of objects trajectory, relative velocity, range and phase angle from scudo observatory

About 50% of these objects were observed by SCUDO observatory and 10 objects with interesting light curves were selected among them. In

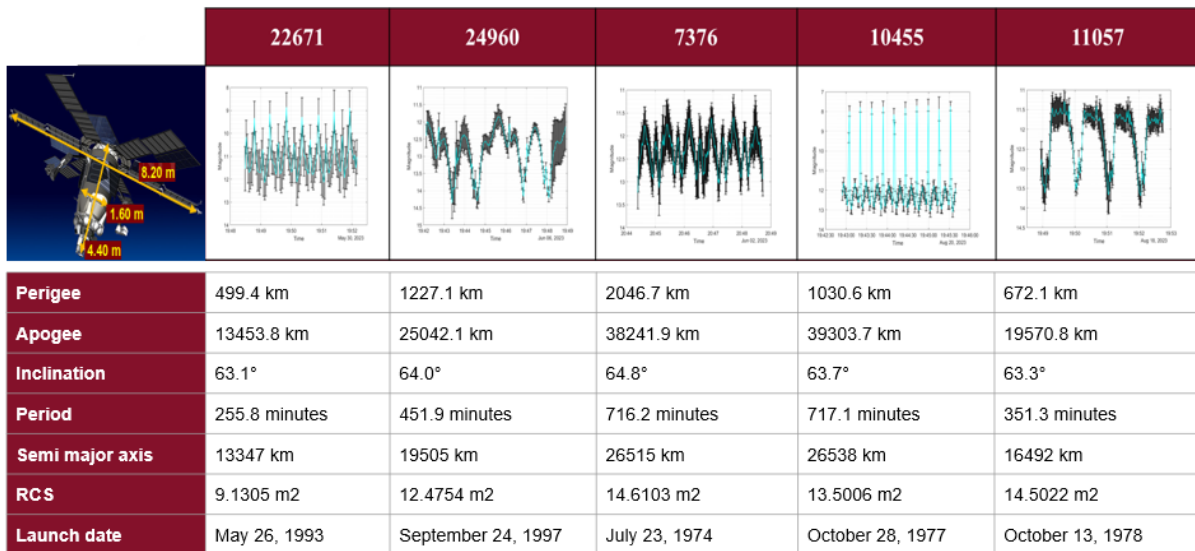


Figure 122 and Figure 123, the acquired light curves from ASI of the 10 targets are shown, displaying the satellite buses and various orbital/physical characteristics. SCUDO acquired approximately 2500 astrometric and photometric measurements for the 10 targets between July and August 2023.

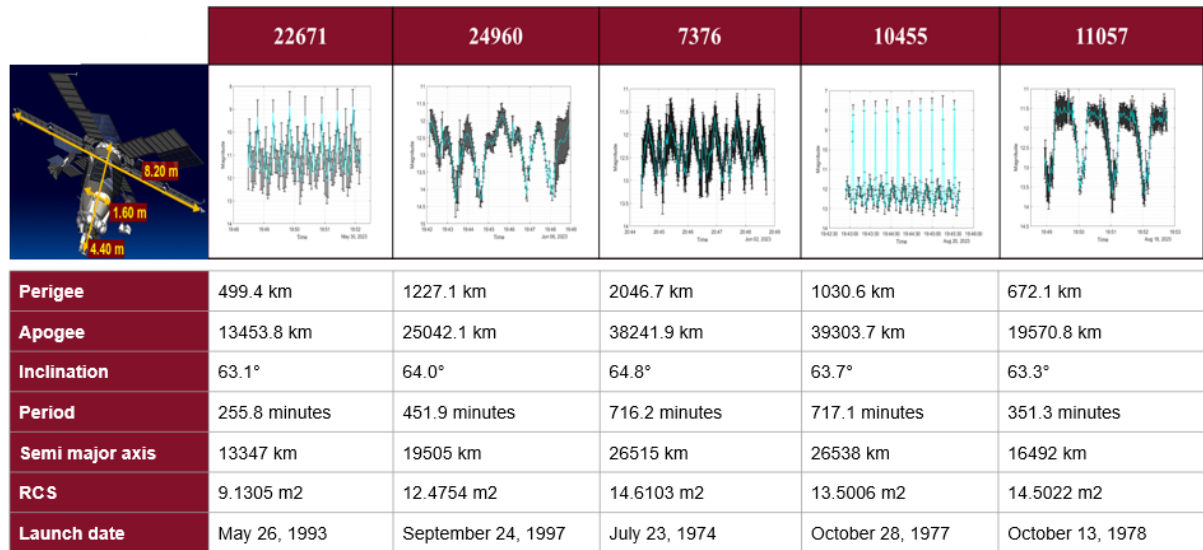


Figure 122. Five Molniya targets with same KAUR-2 satellite bus.

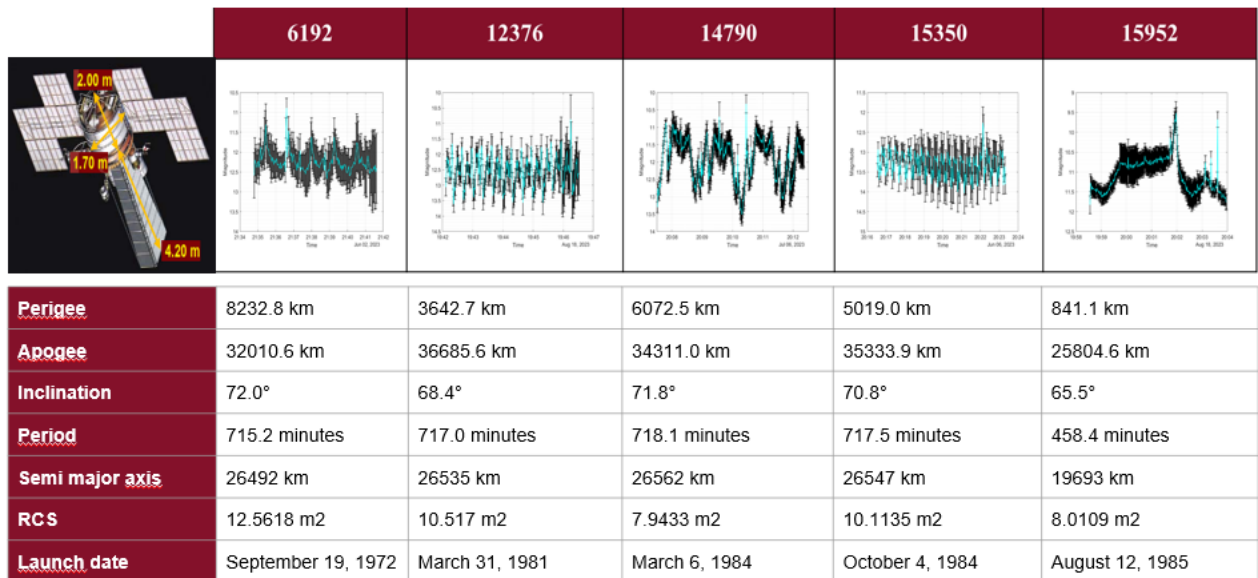


Figure 123. Five Molniya targets with the Oko satellite bus.

The videos obtained are made of single images acquired by SCUDO during the tracking of the object in the apogee phase. The exposure time has been varied according to the altitude of the satellite, i.e. lower altitudes correspond to shorter exposure times. The objects whose curves show a periodic trend would be interesting to be observed again so they are rescheduled for future observations in the long terms planning; in fact, this trend suggests an uncontrolled motion for satellites that are no longer operational.

Figure 124 also illustrates the variations in the orbital parameters derived from the historical TLE data collected for the 10 selected targets. This analysis highlights that the orbits of these objects are not stable and exhibit significant evolution over time.

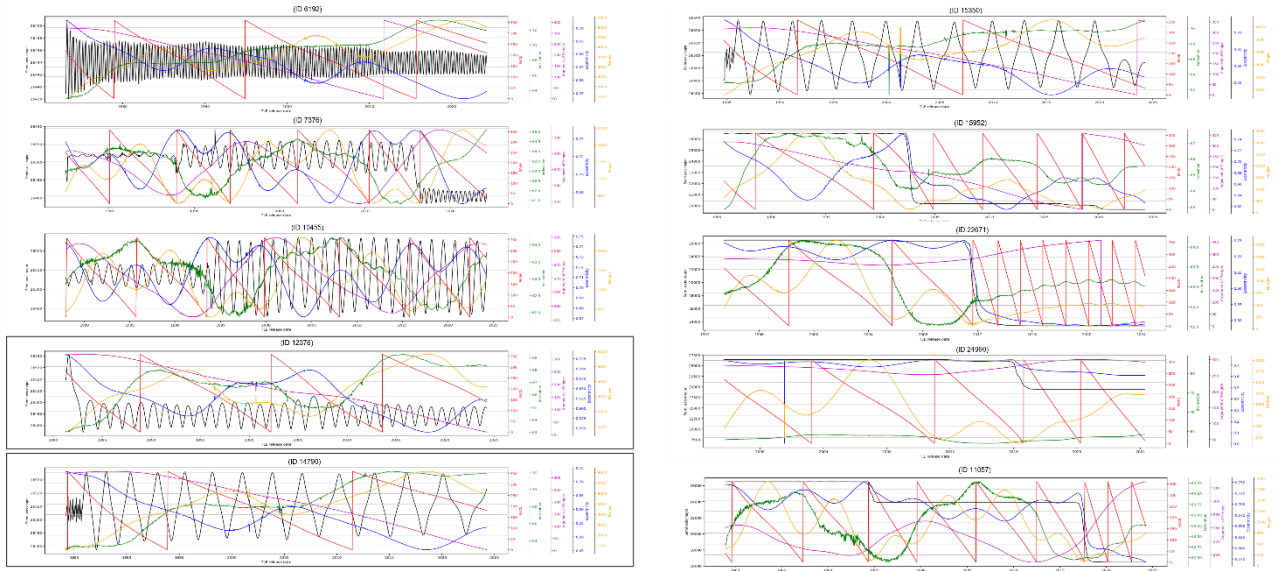


Figure 124. Orbital parameters evolution of the 10 targets

The observed changes demonstrate that these orbits are influenced by a range of perturbative forces, including gravitational interactions, solar radiation pressure, and atmospheric drag, depending on the orbital regime. Moreover, the evolution of these orbits appears irregular and challenging to predict with high precision, reflecting the complex dynamical environment in which these objects exist. This unpredictability underscores the importance of regularly updating orbital parameters and continuously monitoring the behaviour of such objects to ensure accurate tracking and analysis. To perform orbit determination on these objects, it is necessary to acquire measurements both when they are at apogee and when they are at perigee. To observe as many objects as possible during a single night, it is advisable to limit the number of observations per object. For this reason, instead of continuously observing the object for an extended period while it is at apogee, it is preferable to observe it twice during the same pass, leaving a temporal interval between observations. This also extend the observed arc of the orbit. During the perigee phase, continuous observation of the object is required, aiming to acquire as many measurements as possible. To

conduct an analysis of attitude motion, on the other hand, long-duration observations for each object are needed, as variations in the light curve are intended to be analysed. Therefore, astrometric and photometric analyses must be carried out to obtain data on the orbit and attitude motion. Since there is no interest in evaluating the magnitude of these objects, it is preferable to use flux curves (in ADU) over time to estimate the rotation period.

9.5.2. *Results*

For an uncontrolled space object, one of the primary expectations is the achievement of a "flat-spinning" regime around the object's major axis of inertia. The consequences of these perturbations include the precession of the spin axis, which means the axis around which the satellite spins slowly changes direction over time. Additionally, there is a gradual slow-down of the spin period, meaning the time it takes for the satellite to complete one full rotation around its spin axis increases. So, observing the peculiar tumbling motion of the Molniya objects through the years and the evaluation of the differences among their light curves can provide useful information to investigate long term orbital dynamics.

In 2023, during the 41st IADC in Darmstadt, the preliminary results of a precursor observation campaign were presented to understand the availabilities, capabilities, and known object detectability, involving ASI, DLR, and ESA. This campaign included various observational activities and data processing tasks. During the campaign, DLR and ESA, from 15 May 2023 to 26 May 2023, conducted observations from South Africa and Australia, resulting in the acquisition of 194 tracklets, including a few instances of near-simultaneous tracking of the same object. Observations from Switzerland, collected between 15 May 2023 and 7 June 2023, resulted in 239 tracklets, while in Germany, around 1000 images were acquired. Finally, from 30 May 2023 to 9 June 2023, DLR and ESA generated additional tracklets, while ASI acquired 21 videos from telescopes. In the campaign from July 2023 and April 2024 ASI, SSAU and CSA have collected measurements for the 10 targets. In particular, ASI collected

2500 astrometric and photometric measurements from 10 targets, while SSAU collected around 200 light curves over 73 nights and CSA collected space-based measurements of these targets. Can be interesting to examine the light curves of these objects and, if possible, compare them with the ones of satellites launched during the same period that have not changed their period (if available).

9.6. Statistical search observation campaign

9.6.1. Description

The observation of space debris residing at Molniya-type orbits or having transited to orbits similar to Molniya-type is of practical interest because the debris objects that appear at such orbits are caused to break-ups that cross LEO and GNSS orbits. The evolution of such orbits is more complex than of other type of high elliptical orbits and results in transition of apogee location from northern to southern latitudes with crossing GEO operational zone in the interim as shown previously. Propulsion-related breakups, currently the most frequent class, include catastrophic malfunctions during orbital injection or manoeuvres, subsequent explosions based on residual propellants, and failures of active attitude-control systems. Breakups of rocket bodies due to propulsion failures are usually more prolific and produce longer lived debris than the intentional destruction of payloads, often due to the higher altitudes of the malfunctioning rocket bodies rather than the mechanics of the explosive event. The Soviet/Russian Blok-DM Sistema Obespecheniya Zapuska (SOZ) ullage motors have historically exhibited a high probability of fragmentation events. These breakups are a significant concern due to their contribution to orbital debris, particularly in high-altitude orbits (Figure 125).

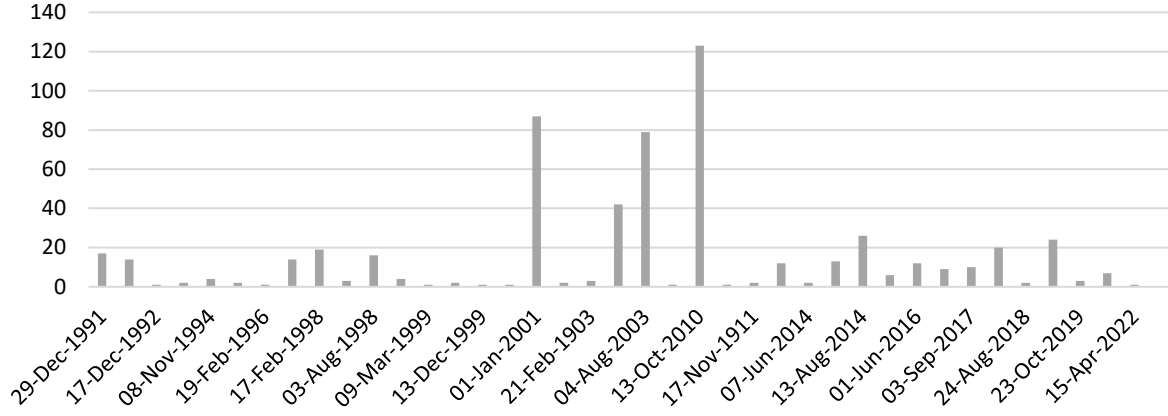


Figure 125. Proton-K Block DM SOZ debris catalogued [66]

Between 1962 and 1986, there were 18 deliberate self-destruction events involving SOZ stages (Figure 126). Additionally, there have been 63 documented fragmentation incidents in Molniya orbits, as reported in [66].

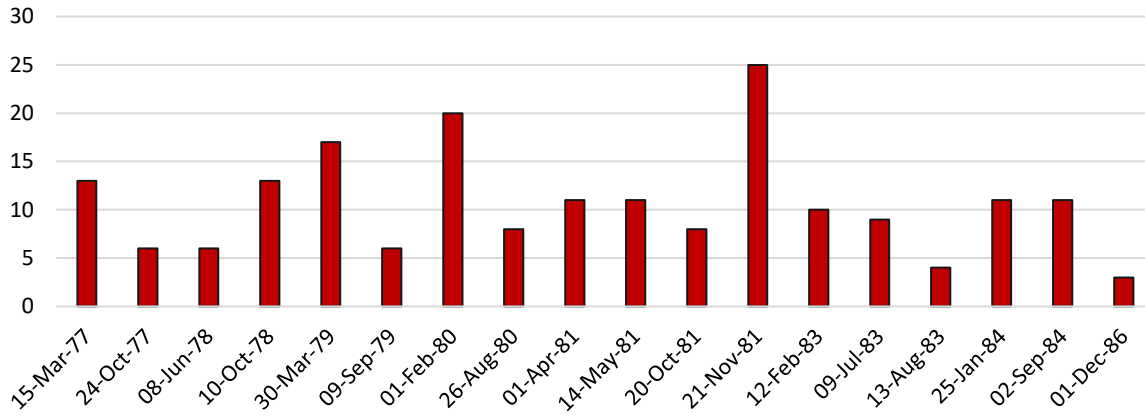


Figure 126. Debris catalogued from deliberate self-destruction [66]

The method presented to identify new objects is based on observe regions in which the current catalogued Molniya apogee density is maximum. The strategy aims to guarantee the acquisition of more than one frame for an object crossing the FoV. The pointing strategy involves scanning a region of sky defined by the considerations obtained through the following calculations.

Example for SCUDO observatory:

- $FoV_{obs} = 1 \text{ deg} \times 1 \text{ deg}$
- $T_{2exp} = 2(exp_{time}) + slew_{time} + time_{readout} = 35 \text{ sec.}$

- $mean_{ang} = 10 \text{ arcsec/sec}$ (Molniya mean angular velocity in apogee)

Considerations:

- $Molniya \text{ dwell time in FoV} = dwell_{time} = FoV / mean_{ang} = 360 \text{ s}$
- $Number \text{ of pointing} = dwell_{time} / T_{2exp} = 10$
- $FoV_{scanned} = floor(\sqrt{tel_{point}}) = 3 \text{ deg} \times 3 \text{ deg}$

The $FoV_{scanned}$ is then divided into subregions and for each of them, two consecutive frames must be taken. Therefore, considering a 3 deg x 3 deg region, 9 different sets of pointing coordinates are used, providing a total of 18 frames. Moreover, the same region must be scanned at least two times. Figure 127 shows the resulted total FoV divided into 9 sub FoV. The starting FoV is represented in green, the centre of the cluster is represented in yellow, the last pointing FoV in red.

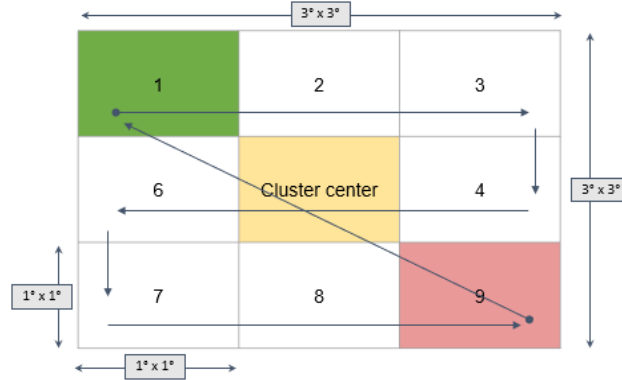


Figure 127. Total FoV scanned for a centroid with indicated the path to follow to observe inside the FoV.

To obtain the region to scan, the first operation is an SGP4 propagation of all the targets in Molniya orbit with consecutive apogee identification as shown in Figure 128. For this propagation a list of TLE of 334 Molniya and Molniya like object was used.

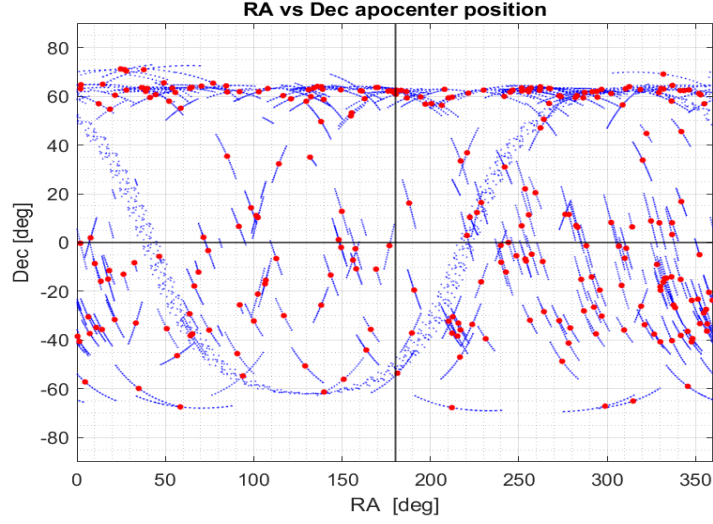


Figure 128. SGP4 propagation and apogee identification for the Molniya-like population.

Then, a clustering algorithm is applied to the apogee distribution, and the centroid for each identified cluster is calculated. The clusters identified in ECI reference frame for north and south hemisphere are shown in Figure 129. This operation is performed separately for both northern and southern hemisphere.

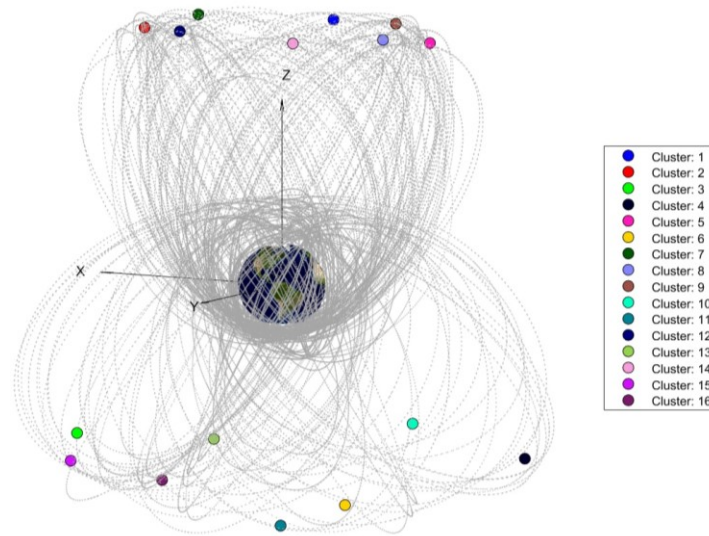


Figure 129. Clusters identified in ECI reference frame for north and south hemisphere.

A certain number of clusters are identified in different regions and selected considering the position of the optical station; then a hemisphere is selected, in terms of declination. This selection is a first skimming of the cluster, to guarantee a high elevation in the observation

visibility condition. The clustering centre is identified, and a ROI is defined considering the estimated FoV for the observation site and the mean time of scanning.

After the definition of the strategy to identify new Molniya object, an international campaign under the IADC was performed with the following guidelines:

- Observation mode: sidereal tracking
- Observation period: from March 18th, 2024, to March 24th, 2024
- Observation duration: 7 days
- Suggested consecutive nights: 3 nights (minimum 2 nights)
- Suggested observation duration: 6 hours/night (minimum 4 hours/night)
- Analysis: astrometric
- ROI acquisition strategy: scanning at least two time the chosen cluster
- Cluster acquisition strategy: at least two consecutive frames for each sub region inside the chosen cluster

ASI has provided each delegation with a folder containing OEM files in ECEF format, specifying X, Y, Z coordinates for each observation date and cluster. This folder includes data for four typical FoVs ($0.5^\circ \times 0.5^\circ$, $1.0^\circ \times 1.0^\circ$, $1.5^\circ \times 1.5^\circ$, $2.0^\circ \times 2.0^\circ$). This shared folder facilitates the selection of observation dates based on weather conditions and station availability. Agencies have the flexibility to choose clusters based on observatory location and select the closest FoV relevant to their specific observatory setup. Additionally, for each day and cluster, a map in geographic coordinates illustrating the ground tracks of the cluster is provided, aiding agencies in their cluster selection process as shown in Figure 130.

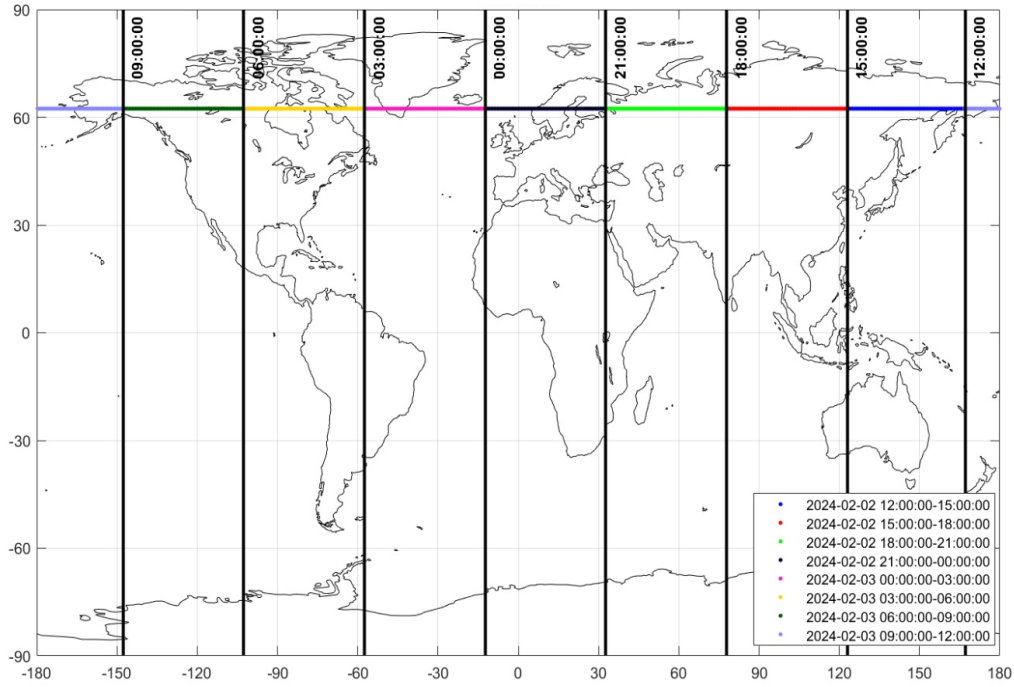


Figure 130. Map in geographic coordinates illustrating the ground tracks of the cluster

During the planned week for the observational campaign, there was a nearly full moon, however, due to various logistical considerations and the upcoming full moon that week was the only available window before April.

9.6.2. Results

Three nights of observation were dedicated to validating the survey strategy, focusing on observing a specific cluster during the nights of August 26th, October 13th and 14th, 2023, for a total of around 24 hours from SCUDO observatory. An additional eight nights of observation were allocated to verify the statistical search strategy, utilizing both cameras available at the SCUDO observatory. During the second attempt, observations were extended to include five clusters. In Table 28 are reported the results of the analysis of the SCUDO acquisition with the first camera setup boasts a FoV of 1.08-by-1.08 degrees (CAM1), while the second setup covers a larger FoV of 1.20-by-1.72 degrees (CAM2).

Table 28. SCUDO data analysis results for the statistical search campaign

Observation date	Cluster	Observation duration	Total Frames		Tracklets number		Catalogued detected		UTCs	
			CAM1	CAM2	CAM1	CAM2	CAM1	CAM2	CAM1	CAM2
2023-08-26	4	7.5 h	1440	N/A	18	N/A	14	N/A	4	N/A
2023-10-13	5	7.5 h	840	N/A	12	N/A	8	N/A	4	N/A
2023-10-14	1	8.5 h	1020	N/A	38	N/A	15	N/A	23	N/A
2024-01-29	6	8.5 h	1000	1050	19	14	12	5	7	9
2024-01-30	6	6.5 h	736	750	15	12	8	6	7	6
2024-01-31	6	10.5 h	1269	1290	42	30	21	20	21	10
2024-02-02	6	10.0 h	872	1835	43	81	39	71	4	10
2024-02-03	6	10.5 h	964	1928	38	139	24	90	14	49
2024-02-14	2	10.0 h	848	1711	34	108	31	69	3	39
2024-03-19	2	8.5 h	N/A	1434	N/A	38	N/A	7	N/A	31
2024-03-20	2	5.5 h	N/A	916	N/A	30	N/A	11	N/A	19

Figure 131 illustrates the acquired measurements in terms of topocentric RA and Dec, organized by observation date and grouped into clusters. This representation provides an overview of the distribution of measurements across different clusters. In the subsequent Figure 132, detailed zooms on three clusters with the highest number of measurements are presented.

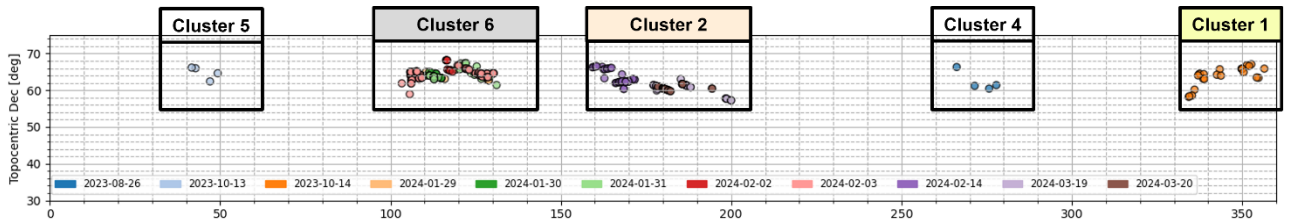


Figure 131. Acquired measurements in term of topocentric RA and Dec divided by date and cluster

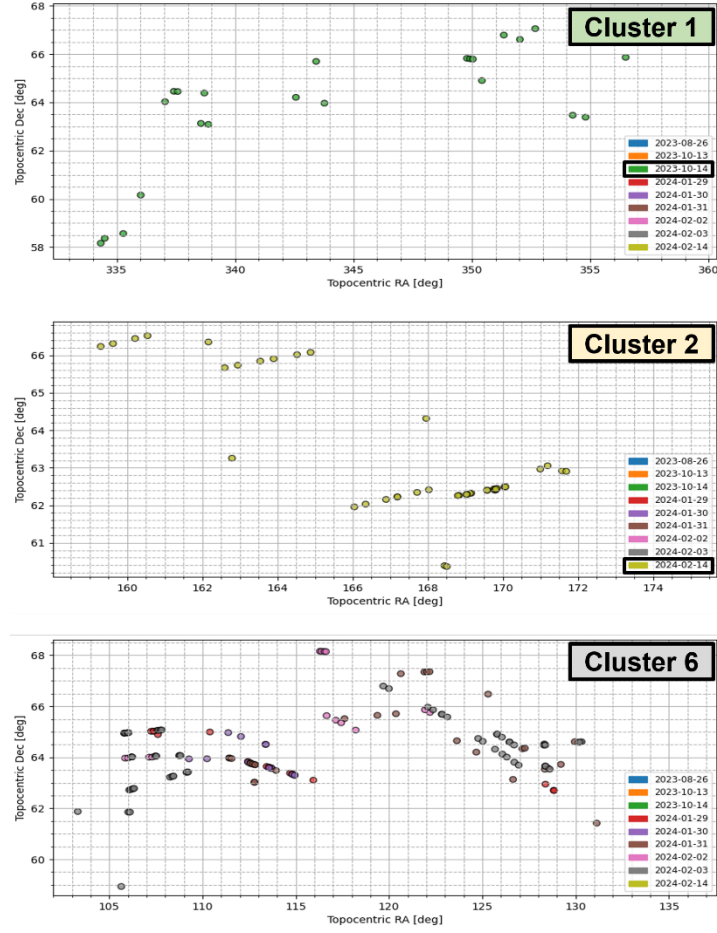


Figure 132. Highlights of cluster 1, 2 and 6

Following the association process of all the collected measurements, a total of 56 distinct objects were identified, as depicted in Figure 133. Among these, particular attention is drawn to Cluster 6, which is highlighted in a detailed zoom in Figure 134. This cluster stands out as the one with the highest number of measurements and the greatest density of objects, making it the most significant for further analysis.

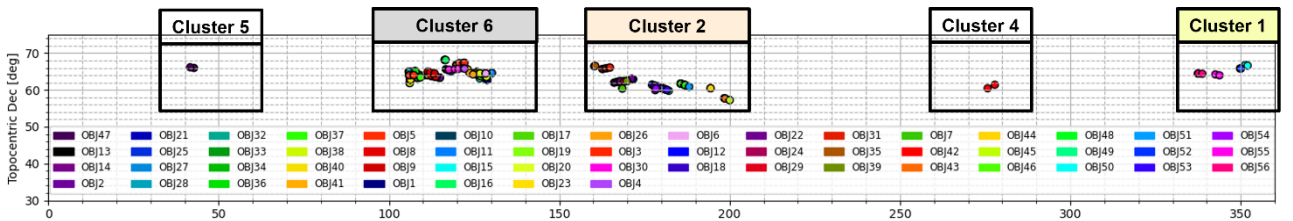


Figure 133. All measurements acquired in the campaign divided by object

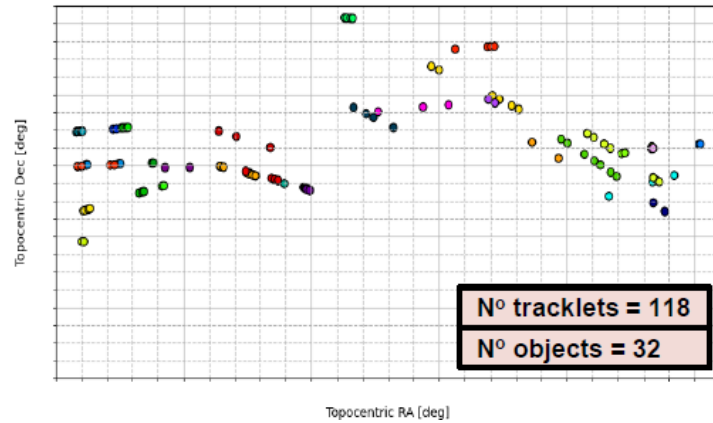


Figure 134. Cluster 6 measurements divided by different objects

Since the measurements for each object range from two to a maximum of six, collected over short time intervals, the orbit determination process tends to yield low-accuracy results. However, given that the observation strategy ensures at least two measurements per object, it is worth investigating a two-point IOD method capable of producing elliptical orbits. To this end, the Väisälä method was applied to assess the feasibility of scheduling a perigee observation following the initial detection during an apogee pass. This approach involves IOD, scheduling, and re-observation from another observatory to refine the orbit estimation. Figure 135 provides an example, showcasing the observation of two objects: one located near apogee and another closer to the apogee region.

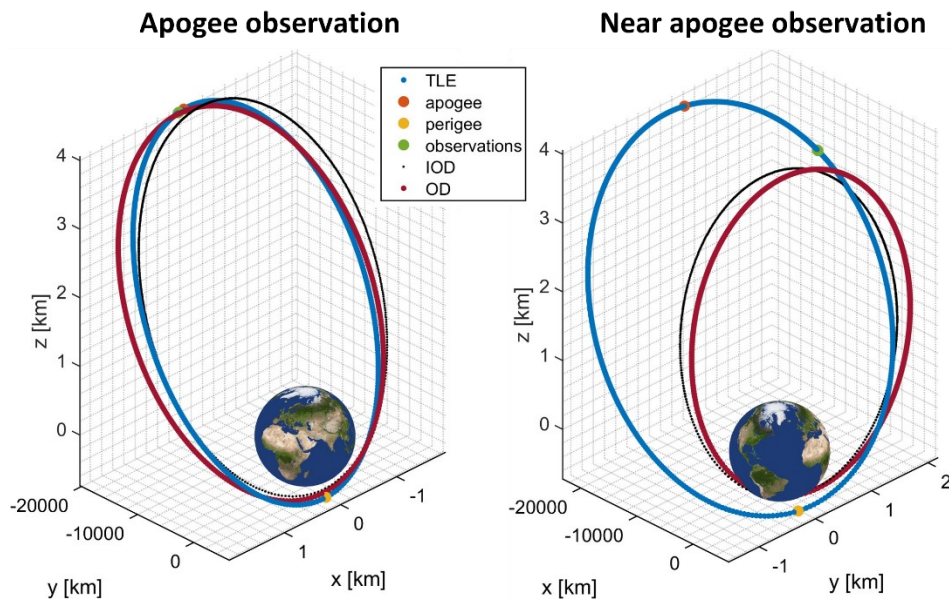


Figure 135. Väisälä method test with a catalogued object in Molniya orbit with observation at the apogee (left) and near the apogee (right)

The results demonstrate that when an object is observed near its apogee, it is possible to retrieve a reasonable orbit from the measurements. However, a significant challenge arises from the fact that it is not possible to know a priori whether the observation of an uncatalogued object corresponds to its apogee. Although the observation strategy targets regions where the density of apogees is highest, there is no guarantee that the object will actually be captured precisely while it is at its apogee. This uncertainty introduces a level of unpredictability in the effectiveness of orbit determination, especially for objects with limited or irregular observations.

10. Conclusions and future developments

This thesis has presented an extensive investigation into observational systems, data analysis methodologies, and applications for satellite and space debris tracking.

The study encompassed the design, implementation, and application of three observational systems: two telescopes, SCUDO and AWARE, and a digital camera system, Mini-SURGE. While SCUDO is based in Italy, both Mini-SURGE and AWARE are located in Western Australia. The systems were described comprehensively from both hardware and software perspectives. For AWARE, the analysis included the factory acceptance tests, the installation process, and subsequent operational deployment. For Mini-SURGE, the focus was on its design, preliminary testing, and installation.

The innovative optical system Mini-SURGE was installed in Geraldton, Western Australia, and is now operated remotely by the S5Lab team at Sapienza University of Rome. Observations are scheduled and conducted periodically. Both astrometric and photometric analyses have been applied to the captured images, and the integration of RGB colour sensors has

enabled simultaneous photometric characterization of objects across three colour channels. This capability, typically achievable only through simultaneous observations with multiple telescopes or sensors, represents a significant advancement. Mini-SURGE has demonstrated its effectiveness as a valuable tool for SSA and SST initiatives thanks to its wide field of view that facilitates the simultaneous observation of dozens of GEO objects, enabling continuous monitoring of large portions of the GEO region. Moreover, Mini-SURGE's compact and cost-effective design ensures its adaptability to a variety of projects. While its measurement accuracy is lower than that of larger telescopes, it serves as an efficient detector for identifying targets, enabling subsequent targeted observations with higher precision observatories.

A key component of this research was the development and utilization of FATE, a dedicated software framework for frame analysis. The architecture of FATE was thoroughly detailed, alongside a step-by-step explanation of its processes, which transform raw frames into usable datasets. These datasets are then shared in the form of TDMs. Additional functionalities of the software were explored, including routines for correlating observations with a public NORAD catalogue, extracting light curves using various photometric filters, and calibrating the time bias across observatories. The centroid calculation method has proven to be effective during typical observation nights and has been successfully implemented to analyze images from the AWARE cameras in real-time. Over the course of 5 months of observations, a total of 265 objects were tracked, generating approximately 30,000 measurements stored across 1,000 TDMs. The detection rate, calculated by dividing the number of measurements by the number of frames (without accounting for multiple detections in a single frame), averaged around 85% for the primary camera and 75% for the secondary camera. In collaboration with the ESA Expert Centre, an observational campaign was conducted to assess the operational performance of the telescope in relation to KPIs. The campaign, conducted by AWARE on July 31, 2023, was considered a success, as it met all the objectives of the validation process and provided a sufficient amount of reduced data to the Expert Centre. The

campaign highlighted several strengths of the system, such as its low latency and robust miss-correlation performance.

The application of a neural network for object detection in image analysis was also investigated and implemented in FATE. Results from the training process and details of the dataset used were presented, highlighting the effectiveness of this approach. The results of sidereal tracking demonstrate promising outcomes across both star and object. For the Star class, the model achieves a precision of 0.628 and a recall of 0.792, yielding an mAP50 of 0.712 and an mAP50-95 of 0.386. These results indicate a solid ability to detect stars, with opportunities for further refinement, particularly in enhancing precision and performance under stricter evaluation metrics. The Object class, however, showcases exceptional accuracy, achieving a precision of 0.972 and a perfect recall of 1.000, ensuring that all objects were successfully identified. This outstanding performance is reflected in a mAP 50 of 0.994 and an mAP50-95 of 0.838, confirming the model's reliability even under more rigorous assessment criteria. Further analysis included a comparative evaluation between the proposed YOLO v5 algorithm and the deterministic ASTRIDE approach, revealing notable differences in both detection capabilities and computational efficiency. YOLO v5 successfully identified objects in all 78 frames (100%) without any false detections, whereas ASTRIDE detected only 56% of the objects, missing 44% of the targets, and introduced 46 false positives. In terms of processing speed, YOLO v5 demonstrated a significant advantage, achieving an average processing time of 1.1 seconds per frame compared to ASTRIDE's 4.2 seconds, making it nearly four times faster overall. While YOLO v5 exhibited superior performance in this comparison, achieving 100% detection accuracy and zero false positives is not guaranteed across all scenarios. These results underscore the advantages of the proposed algorithm in terms of both precision and efficiency, while highlighting areas for ongoing improvement and adaptation to diverse observational conditions.

Using the TDMs generated from observations, the thesis detailed the application of IOD and OD procedures to derive orbital parameters. One example involved the high-LEO satellite LARES, where OD accuracy was assessed using data from a single pass, two passes within the same day, and three passes spread over two days. Another case study focused on a Molniya orbit object with high eccentricity, observed over a three-hour window. The feasibility of tasking a second observatory (SCUDO) based on predictions derived from OD data obtained by AWARE was also explored. An additional example demonstrated the workflow for Mini-SURGE, starting from measurement acquisition to the identification of both catalogued and uncatalogued objects, association of observations, and OD for unknown targets. The multi-site orbit determination was tested using data from two observatories, focusing on the Molniya object with NORAD ID 22671. Observations were carried out using two contrasting strategies: AWARE captured 80 measurements over four 1-minute intervals, while SCUDO collected 700 measurements during a single 12-minute session. SCUDO observed the orbital pass immediately following the one tracked by AWARE. The objective was to evaluate whether OD results from AWARE could sufficiently initialize SCUDO's observations, which were originally based on TLE data. The differences in terms of RA/Dec coordinates, showing that the OD data from AWARE enabled SCUDO to successfully track the object with greater accuracy than TLE data. The differences between SCUDO's measurements and AWARE's OD results were smaller than those between SCUDO's measurements and the TLE predictions. Incorporating an additional pass enhanced the dataset, allowing the OD process to converge in four iterations with improved accuracy in the estimated orbital parameters. Comparing results from both dates revealed substantial improvements in position and velocity vectors, emphasizing the advantage of combining observations from multiple passes to achieve higher precision in orbit determination. For Mini-SURGE, 14 unknown objects were identified within the field of view on March 4, 2024. Analysis of the RAAN versus inclination plot showed catalogued objects clustering tightly at low inclinations, consistent with geostationary orbits. In contrast, unknown objects exhibited a broader range of inclinations. Similarly, in the semi-major axis versus eccentricity plot, catalogued

objects were concentrated near a semi-major axis of approximately 42,000 km with near-zero eccentricities. Unknown objects, however, displayed a wider range of eccentricities, reaching values as high as 0.35, with slight variations in their semi-major axes. These findings highlight a clear distinction between catalogued and unknown objects, particularly in the semi-major axis versus eccentricity plot.

Beyond orbital analysis, this thesis proposed an innovative method to derive attitude parameters from light curves, data that are generally unavailable for space debris and many other artificial objects in orbit. A case study was performed using simulated scenarios to retrieve an objective light curve through the application of a genetic algorithm. Three separate cost functions were tested, as well as their combination using a MOGA. Individually, none of the three cost functions delivered satisfactory optimization outcomes. Each process took slightly over an hour and a half, but the narrow focus of each cost function on specific aspects of the light curves hindered a comprehensive optimization of multiple criteria. In contrast, the MOGA approach delivered robust results, showing strong agreement between the simulated and observed light curves. The optimization required approximately 1 hour and 42 minutes to complete, which is reasonable given the complexity involved. The retrieved attitude parameters, including orientation angles and angular velocities, were determined and closely matched the target values. This confirmed the effectiveness of the MOGA in finding solutions consistent with the expected results. In the real case study, although the predicted and observed light curves were not perfectly identical, their similarities were significant, especially in the alignment of their peak features. Differences could be ascribed to several uncertainties, such as limitations in the accuracy of the object's 3D representation, including its shape, inertia, construction materials, and potentially unmodeled environmental effects. These factors influence how the object reflects or scatters light, thus impacting the light curve. Despite these limitations, the optimization succeeded in identifying an attitude solution consistent with the observed data. The strong correlation between the two light curves validated the proposed model under the conditions studied. To further

advance the evaluation of the light curve inversion algorithm, a performance analysis could be conducted under varying noise conditions to assess its robustness and accuracy. Synthetic light curves would be generated with predefined parameters, and progressively higher levels of noise could be introduced to simulate realistic observational scenarios. The MOGA and the Multi-swarm particle swarm might then be applied to estimate attitude parameters for each noisy dataset. The performance could be assessed through two key metrics: the accuracy of parameter estimation and the quality of curve fitting. For parameter estimation, the mean and variance of the errors in the retrieved parameters could be calculated across all noise levels, highlighting the algorithm's sensitivity to noise. Similarly, the curve fitting accuracy might be quantified by analysing the mean and variance of the fitting errors, offering insights into how well the reconstructed light curves align with the noisy input data. It would be expected that, while the algorithm might maintain acceptable accuracy at lower noise levels, its performance could degrade as noise increases beyond a certain threshold. Such an analysis would provide valuable insights into the algorithm's operational limits and its potential to deliver reliable attitude estimates under different observational conditions.

Finally, the thesis included an international observational campaign conducted under the framework of the IADC (Inter-Agency Space Debris Coordination Committee). Since 2022, I have been responsible for coordinating this campaign, defining observational strategies, and liaising with participants from various space agencies worldwide. This campaign demonstrated the applicability of the methodologies developed in this research to global collaborative efforts in space surveillance and tracking. As part of the statistical survey, a list of 10 targets was provided by ASI to WG2 for simulations aimed at understanding the behaviour of fragmentations in Molniya orbits. These simulations sought to reveal how objects with different orbital parameters respond to various perturbations over time. It would be particularly insightful to examine the light curves generated in these simulations by WG2 to identify whether they exhibit unique characteristics or share commonalities.

Additionally, propagating the initial conditions at the start of the operational orbit to analyze the dynamics leading up to the perigee flip could yield valuable insights. Regarding the observational efforts for the statistical survey, ASI, SSAU, DLR, and CNSA conducted coordinated observations during the week of March 18–24, 2024. Specifically, ASI observed for 11 nights, including two nights as part of the joint campaign. SSAU and DLR observed for three nights during that week, while CNSA conducted observations over five days. The analysis of the measurements from all participating agencies could provide a deeper understanding of the consistency and coverage achieved during this campaign.

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Appendix A

Table XX illustrates the Header Section of the TDM, Table XX reports the Metadata Section, and Table 20 refers to the data acquired during the observation. Data appearing in this section cover the time span specified in the Metadata Section, by sequentially repeating the same pattern of keywords but referred to different time tags.

Table 29. TDM header keywords and their description

TDM HEADER SECTION	
Keyword	Description
CCSDS_TDM_VERS	Format version of the TDM
CREATION_DATE	TDM creation date and time in UTC (ISO 8601)
ORIGINATOR	Abbreviation associated to the creating agency

Table 30. TDM Metadata Section keywords and their description

TDM METADATA SECTION	
Keyword	Description
META_START	Start of the TDM Metadata Section
DATA_TYPES	Comma separated types of data provided in the Data Section.
TIME_SYSTEM	It specifies the time scale adopted for the timetags appearing in the Data Section
START_TIME	It specifies the UTC (ISO 8601) start time of the total time span covered by the tracking data
STOP_TIME	It specifies the UTC (ISO 8601) stop time of the total time span covered by the tracking data
PARTICIPANT_1	Station ID as declared in the EU SST Database meaning
PARTICIPANT_2	NORAD ID of the observed object
MODE	Tracking mode associated with the data presented in the Data Section

PATH	Signal path between participants
ANGLE_TYPE	Type of angles observed and reported in the Data Section
REFERENCE_FRAME	It applies only to the ANGLE_TYPE keyword. It indicates the associated reference frame
CORRECTION_TIME_BIAS	It indicates the time bias of the acquisition system in seconds
CORRECTIONS_APPLIED	It indicates if corrections listed above have been applied
WAVELENGTH	It indicate the wavelength employed to acquire data
META_STOP	End of the TDM Metadata Section

Table 31. TDM Data Section

TDM DATA SECTION	
Keyword	Description
DATA_START	Start of the TDM Data Section
ANGLE_1	Angle 1 (as specified in ANGLE_TYPE in the Metadata Section) measurement in deg and its timetag
ANGLE_2	Angle 2 (as specified in ANGLE_TYPE in the Metadata Section) measurement in deg and its timetag
PRESSURE	Pressure in hPa and its timetag
RHUMIDITY	Humidity in % and its timetag
TEMPERATURE	Temperature in K and its timetag
STEC	Slant Total Electron Count in TECU and its timetag
TROPO_DRY	Dry zenith delay through the troposphere measured at the timetag
TROPO_WET	Wet zenith delay through the troposphere measured at the timetag
MAG	Apparent magnitude of the observed object at the timetag
DATA_STOP	End of the TDM Data Section

Caso 1 OD LEO

OD Initial condition

Epoch initial condition [UTC]	2024-05-06T12:32:49.235558
Reference system	ICRF
X, Y, Z [km]	[-4242.565663, 2981.154793, -5869.928383]
VX, VY, VZ [km/s]	[-5.882763, -0.479428, 4.018337]
Reference system	ICRF
dX, dY, dZ [km]	[3.947474, 5.900480, 9.080792]
dVX, dVY, dVZ [km]	[0.015830, 0.004634, 0.009141]
Reference system	RTN
dX, dY, dZ [km]	[6.913393, 8.751526, 2.911152]
dVX, dVY, dVZ [km]	[0.004789, 0.017765, 0.004135]

IOD and OD Classical orbital elements

	IOD	OD
Semimajor axis [km]	7831.223804	7846.187819
Eccentricity	0.000000	0.002072
Inclination [deg]	69.530793	69.514787
RAAN [deg]	169.906570	169.924364
Argument of perigee [deg]	113.566522	337.294368
True_anomaly [deg]	193.313404	329.569929

CASO 2 OD LEO

*** Initial condition (OD):

Epoch initial condition [UTC]	2024-05-07T11:29:44.952095
Reference system	ICRF
X, Y, Z [km]	[-4041.998743, 3103.013332, -5942.885318]
VX, VY, VZ [km/s]	[-5.951645, -0.264354, 3.918742]
Reference system	ICRF
dX, dY, dZ [km]	[0.004927, 0.006098, 0.012943]
dVX, dVY, dVZ [km]	[2.633560e-05, 3.525001e-05, 3.235320e-05]
Reference system	RTN
dX, dY, dZ [km]	[0.010823, 0.006286, 0.008505]
dVX, dVY, dVZ [km]	[4.144803e-05, 1.041857e-05, 3.400545e-05]

IOD/OD Classical orbital elements (IOD):

	IOD	OD
Semimajor axis [km]	7829.101484	7817.910624
Eccentricity	0.000000	0.001641
Inclination [deg]	69.513138	69.514345
RAAN [deg]	168.320237	168.317270
Argument of perigee [deg]	158.583182	91.025692
True_anomaly [deg]	147.276204	214.840203

CASO 3 OD LEO

*** Initial condition (OD):

Epoch initial condition [UTC]	2024-05-07T11:29:44.952095
Reference system	ICRF
X, Y, Z [km]	[-4041.995250, 3103.016101, -5942.839350]
VX, VY, VZ [km/s]	[-5.951664, -0.264387, 3.918778]
Reference system	ICRF
dX, dY, dZ [km]	[0.004624, 0.005945, 0.009789]
dVX, dVY, dVZ [km]	[2.469844e-05, 3.406074e-05, 2.870700e-05]
Reference system	RTN
dX, dY, dZ [km]	[0.008690, 0.004591, 0.007480]
dVX, dVY, dVZ [km]	[3.781744e-05, 7.955486e-06, 3.317817e-05]

IOD/OD Classical orbital elements

	IOD	OD
Semimajor axis [km]	7829.101484	7817.921445
Eccentricity	0.000000	0.001637
Inclination [deg]	69.513138	69.514133

RAAN [deg]	168.320237	168.317326
Argument of perigee [deg]	158.583182	90.866803
True_anomaly [deg]	147.276204	214.999234